By Suren Manvelyan, http://www.surenmanvelyan.com/gallery/7116

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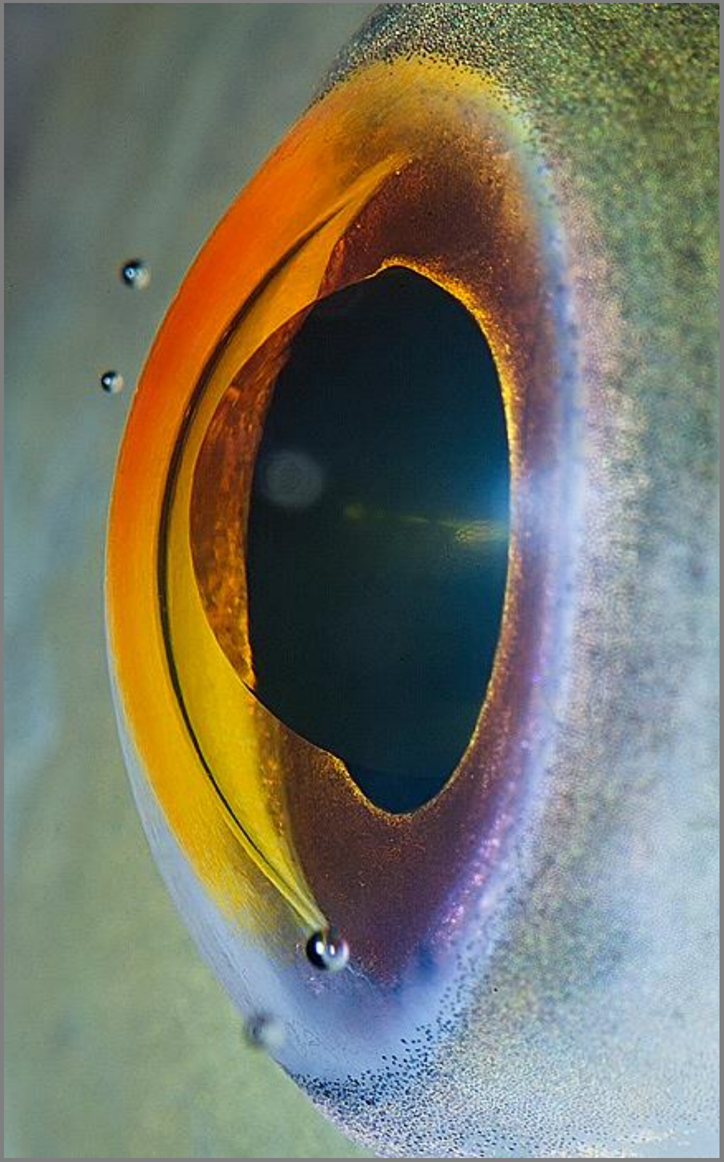

By Suren Manvelyan, http://www.surenmanvelyan.com/gallery/7116

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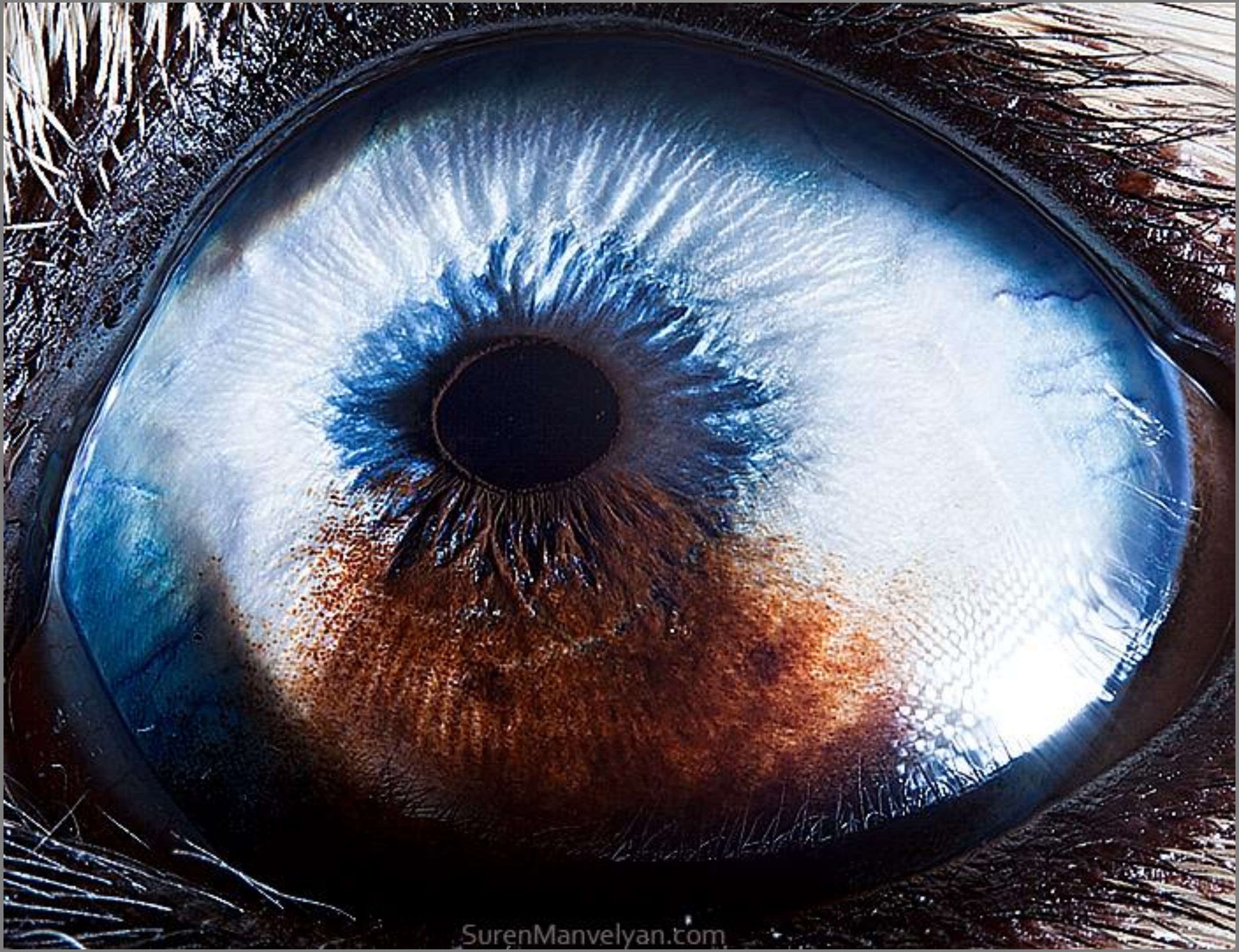


By Suren Manvelyan, http://www.surenmanvelyan.com/gallery/7116

Indy


Indy

Heterochromia iridum

From Wikipedia, the free encyclopedia

Not to be confused with Heterochromatin or Dichromatic (disambiguation).

In anatomy, **heterochromia** (ancient Greek: ἕτερος, *héteros*, different + χρῶμα, *chróma*, color[1]) is a difference in coloration, usually of the iris but also of hair or skin. Heterochromia is a result of the relative excess or lack of melanin (a pigment). It may be inherited, or caused by genetic mosaicism, chimerism, disease, or injury.[2]

Heterochromia of the eye (***heterochromia iridis*** or ***heterochromia iridum***) is of three kinds. In *complete heterochromia*, one iris is a different color from the other. In *sectoral heterochromia*, part of one iris is a different color from its remainder and finally in "central heterochromia" there are spikes of different colours radiating from the pupil.

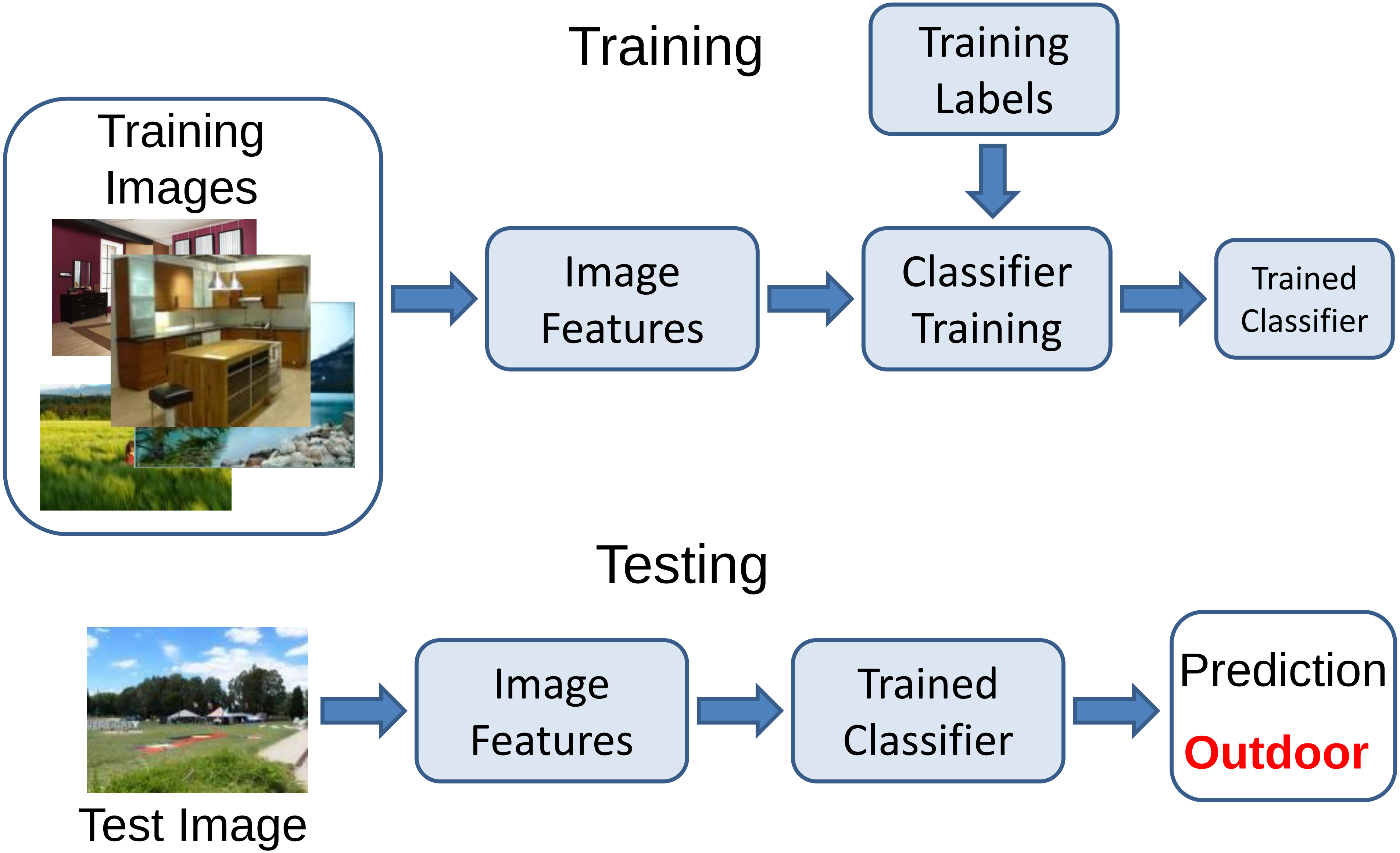
Heterochromia

Complete heterochromia in human eyes: one brown and one green/hazel

Classification and external resources

Specialty	ophthalmology
ICD-10	Q13.2, H20.8, L67.1
ICD-9-CM	364.53
OMIM	142500
DiseasesDB	31289

Image Categorization



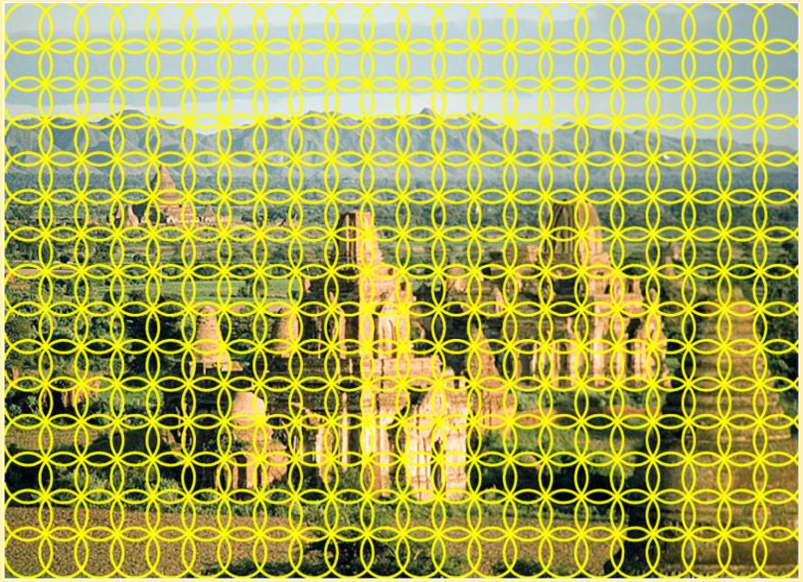
History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features

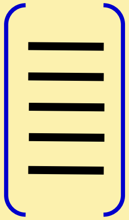
Svetlana Lazebnik

1. Feature extraction

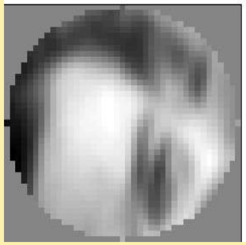
- Regular grid or interest regions



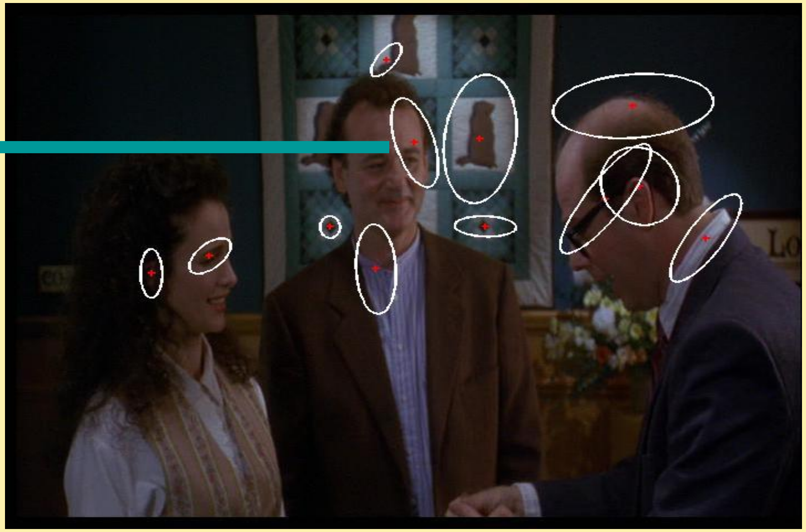
1. Feature extraction



Compute descriptor



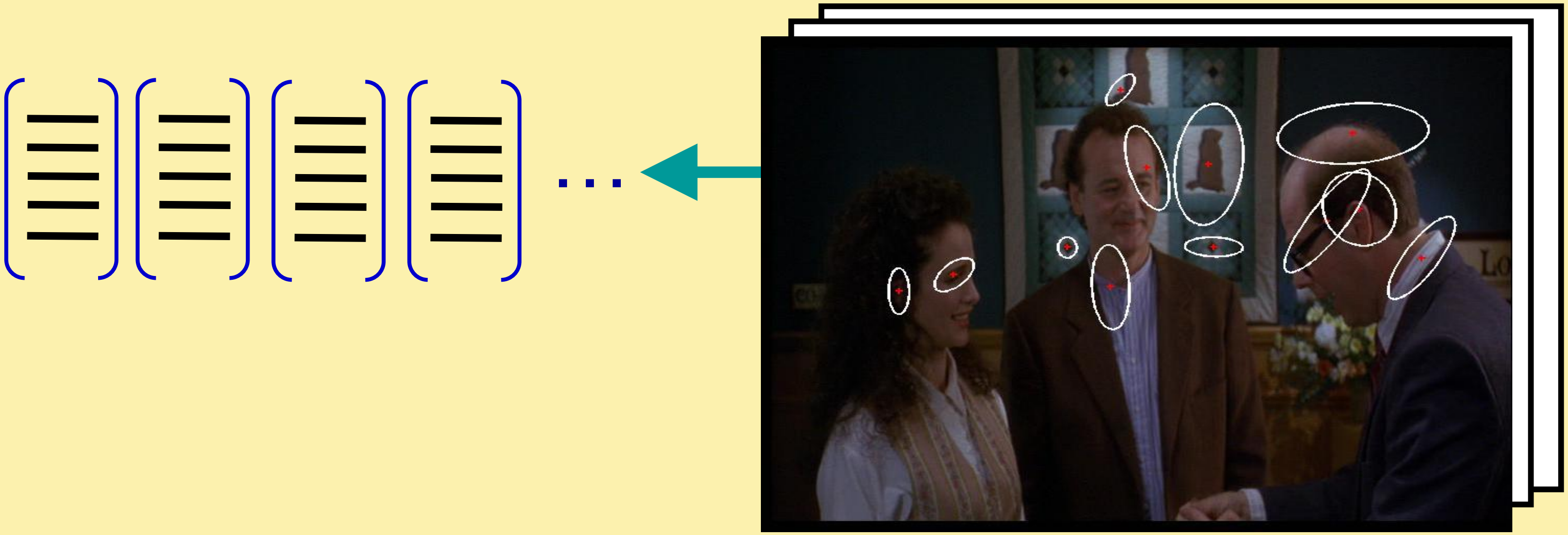
Normalize patch



Detect patches

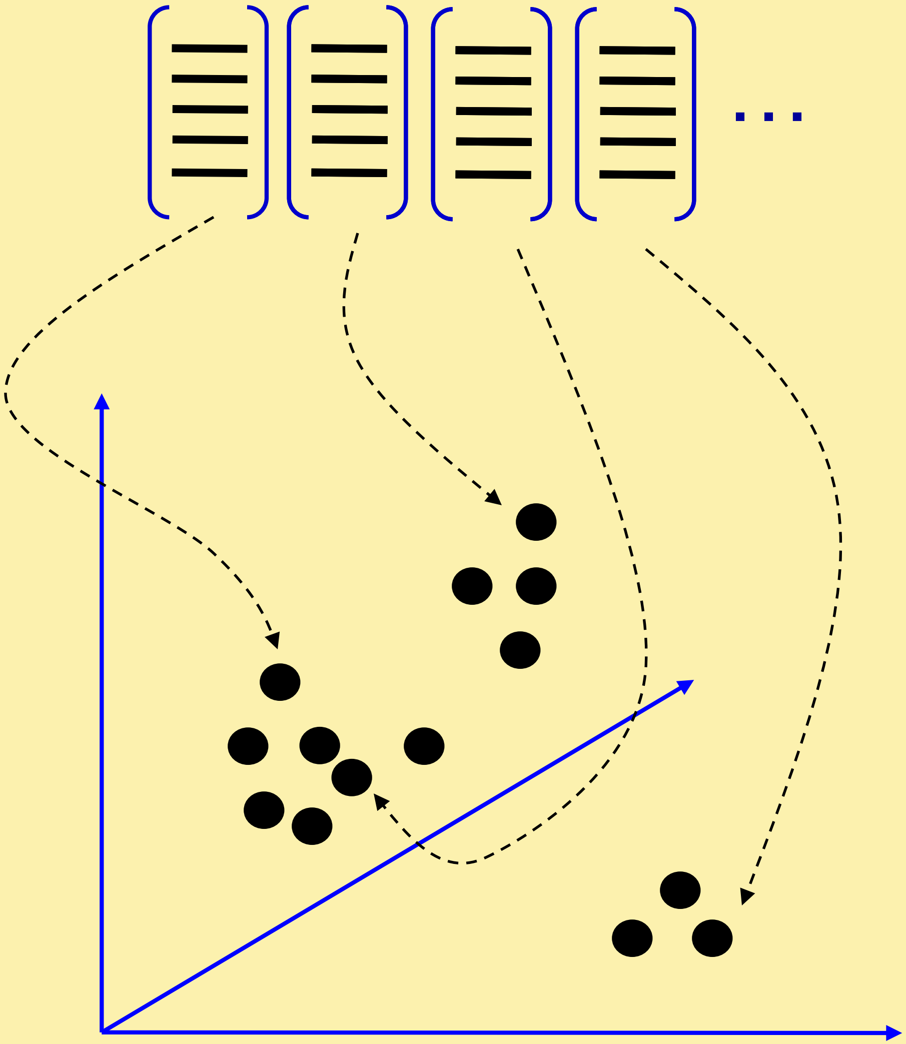
Slide credit: Josef Sivic

1. Feature extraction



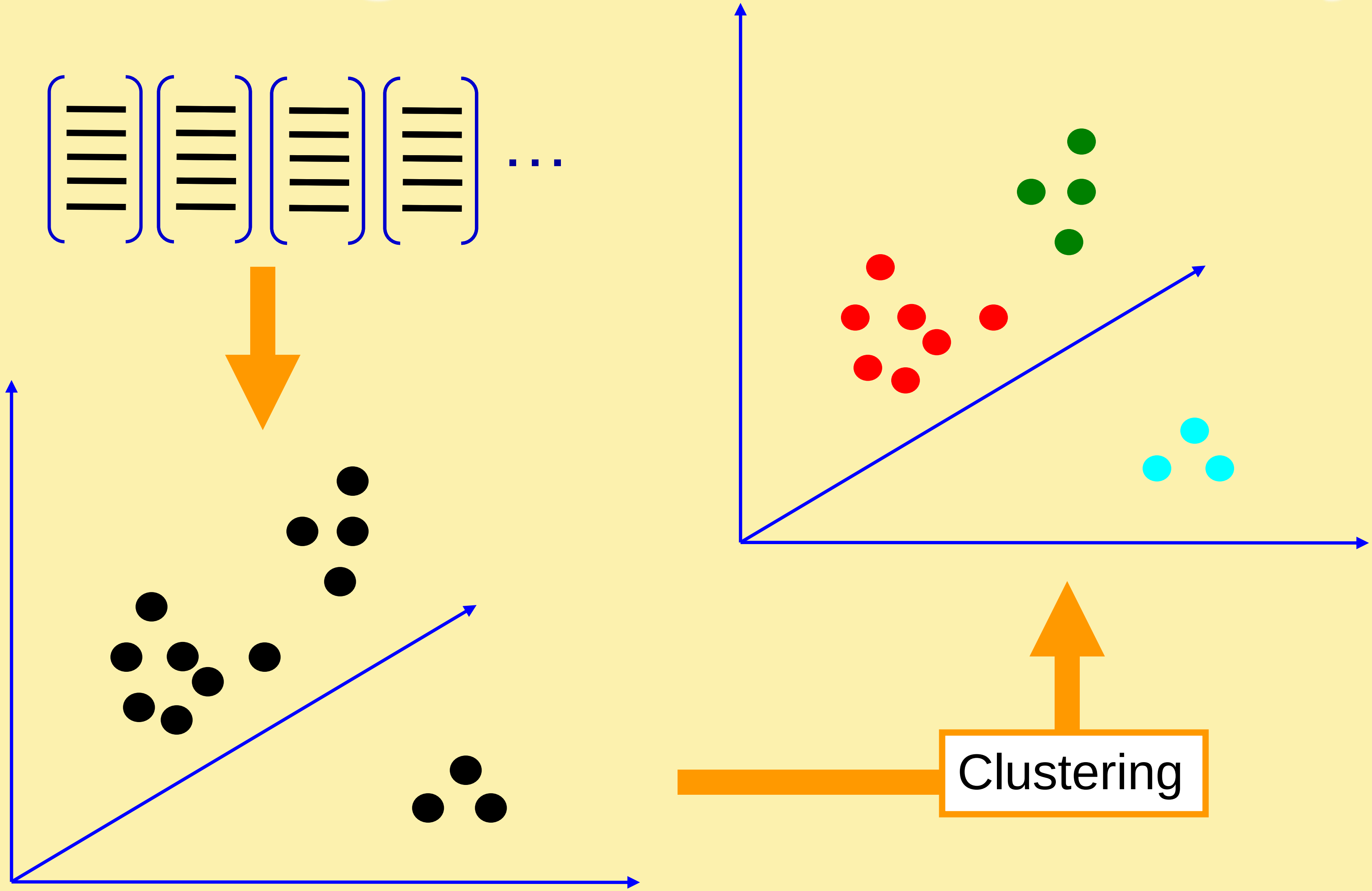
Slide credit: Josef Sivic

2. Learning the visual vocabulary



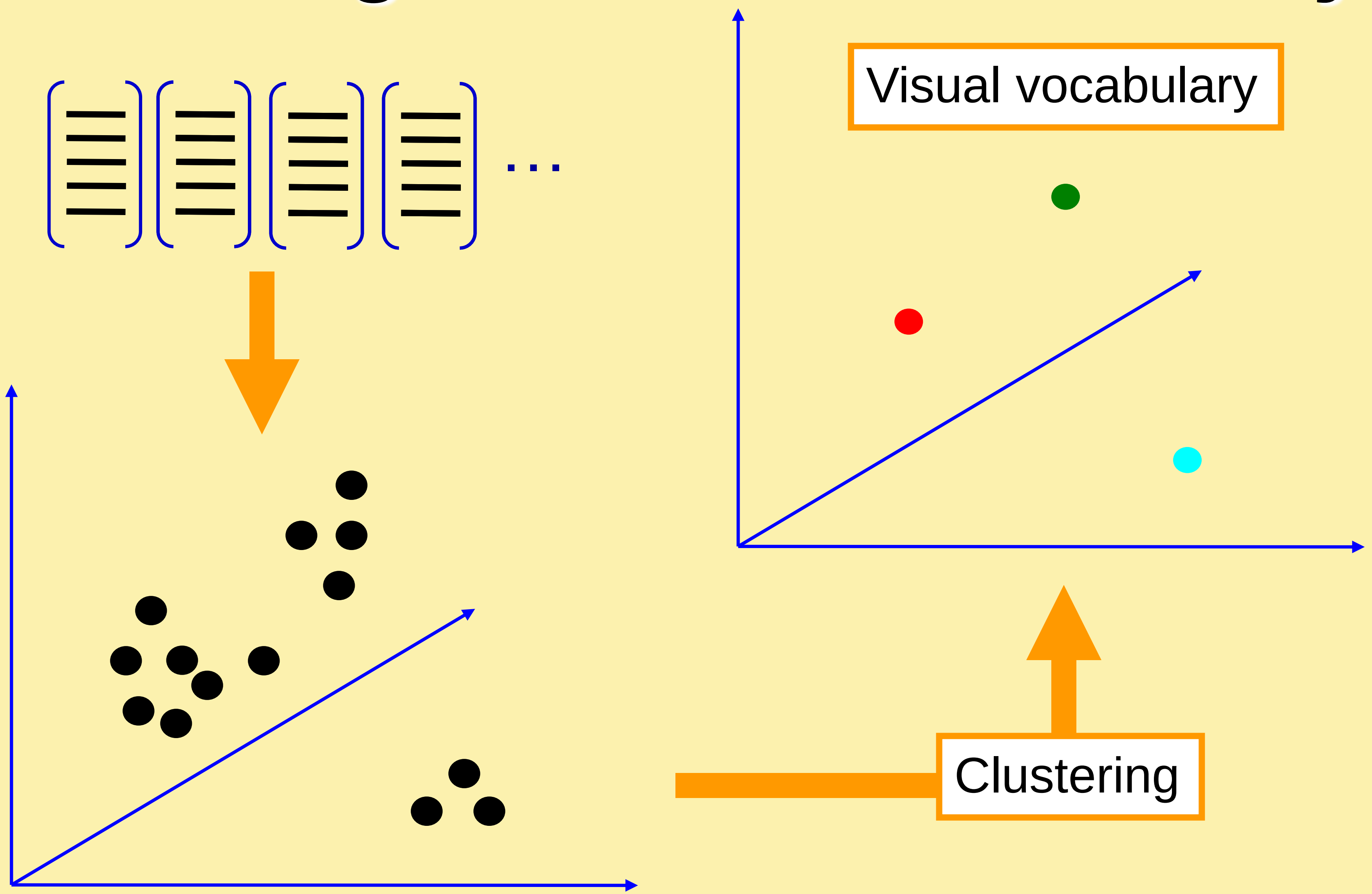
Slide credit: Josef Sivic

2. Learning the visual vocabulary



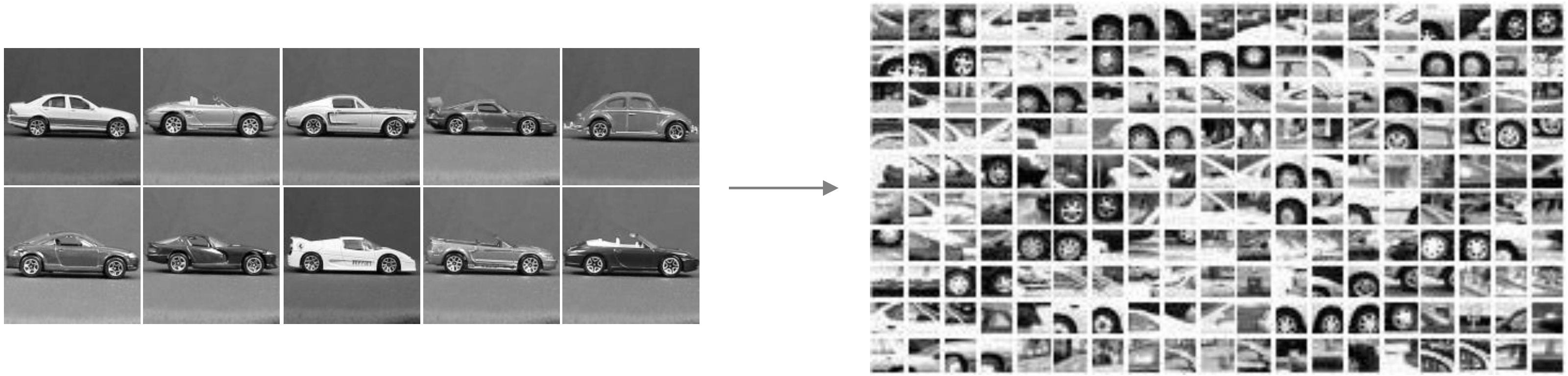
Slide credit: Josef Sivic

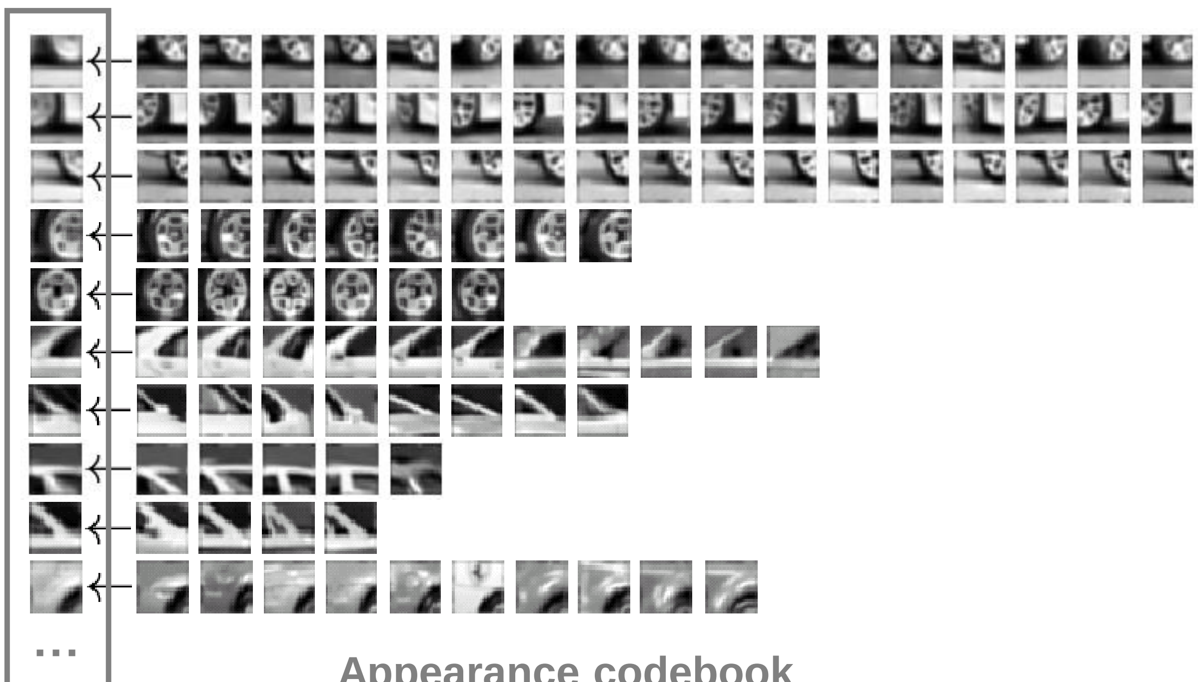
2. Learning the visual vocabulary



Slide credit: Josef Sivic

Example codebook



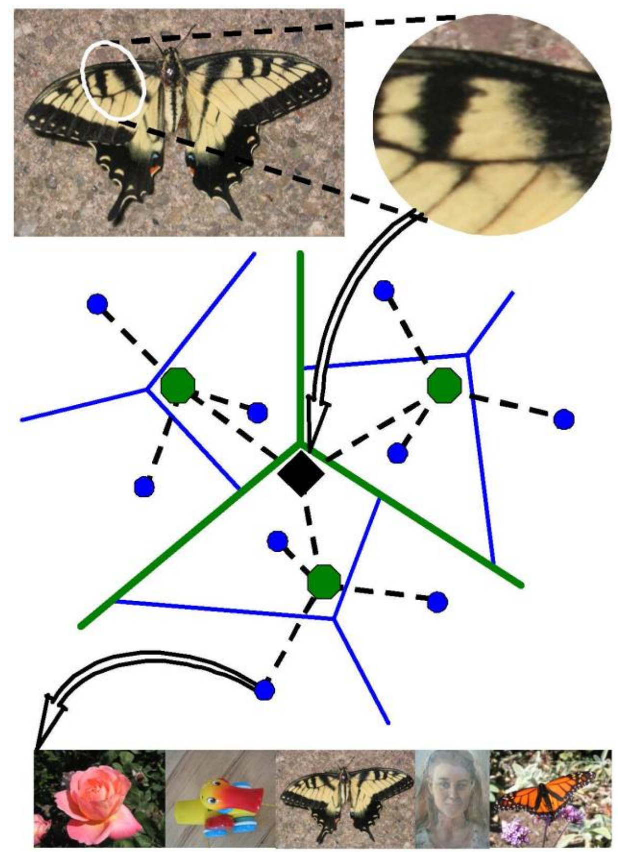


Appearance codebook

Source: B. Leibe

Visual vocabularies: Issues

- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
- Computational efficiency
  - Vocabulary trees
    (Nister & Stewenius, 2006)



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- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features
- Present trends: combination of local and global methods, context, *deep learning*

Svetlana Lazebnik

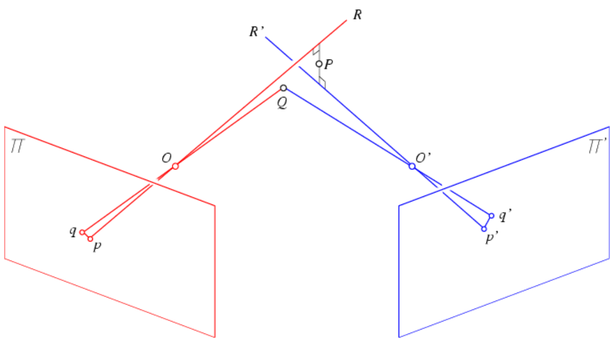
Large-scale Instance Retrieval

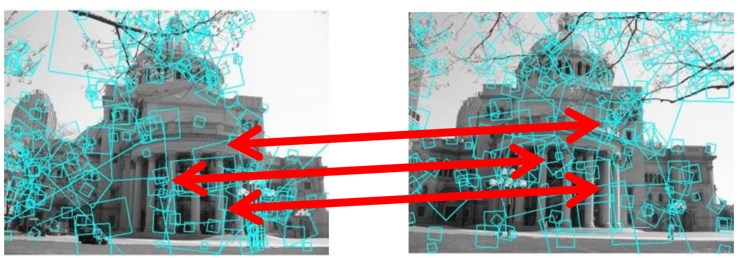
Computer Vision

James Hays

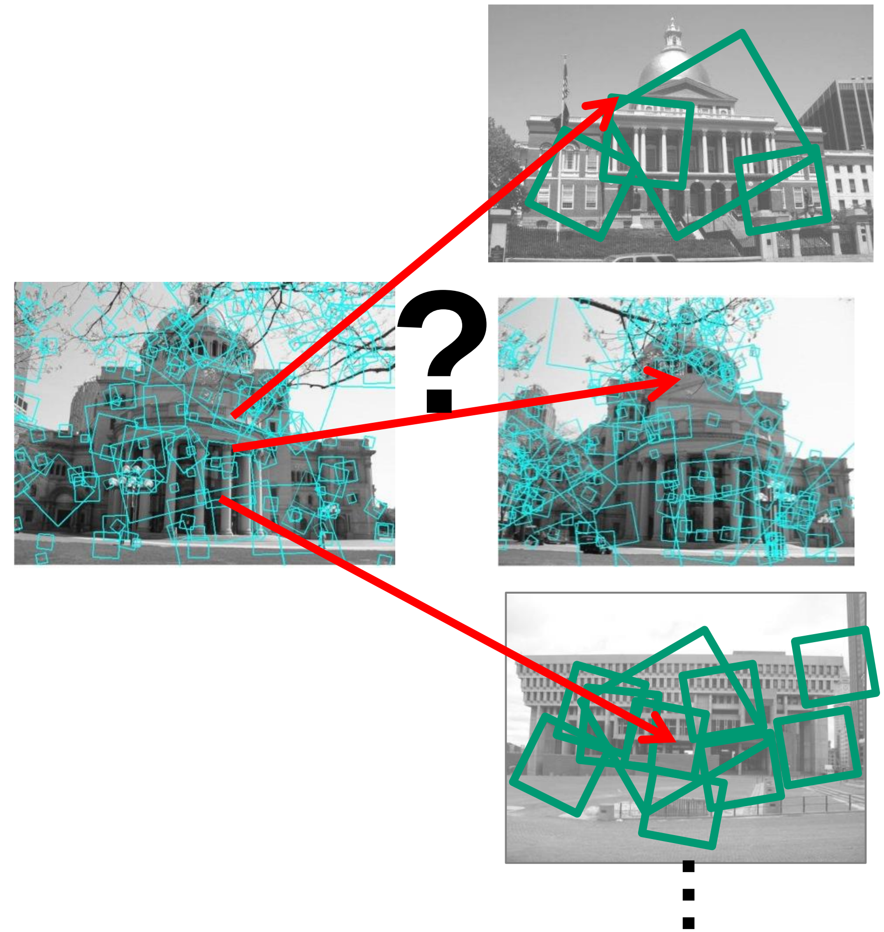
Many slides from Derek Hoiem and Kristen Grauman

Multi-view matching





vs



Matching two given views for depth

Search for a matching view for recognition

Kristen Grauman

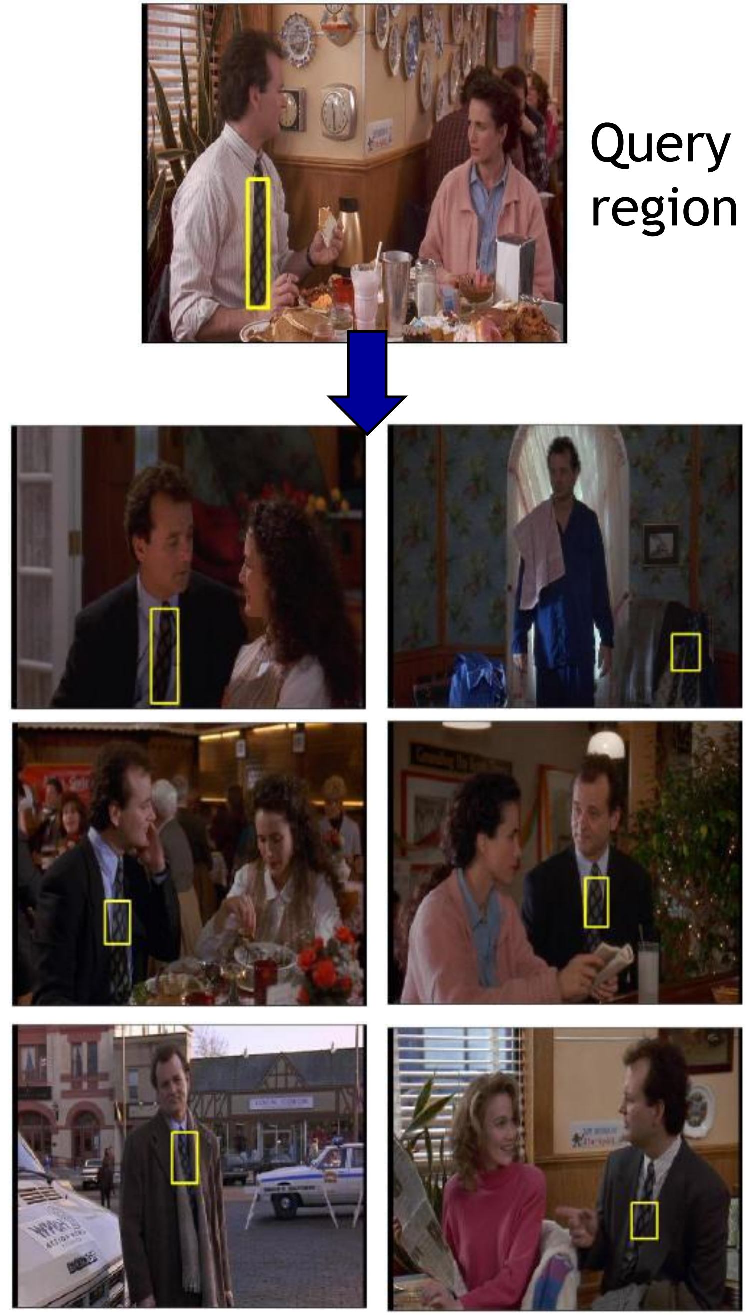
Demo

Video Google System

1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

- **Demo online at :** http://www.robots.ox.ac.uk/~vgg/research/vgoogle/index.html

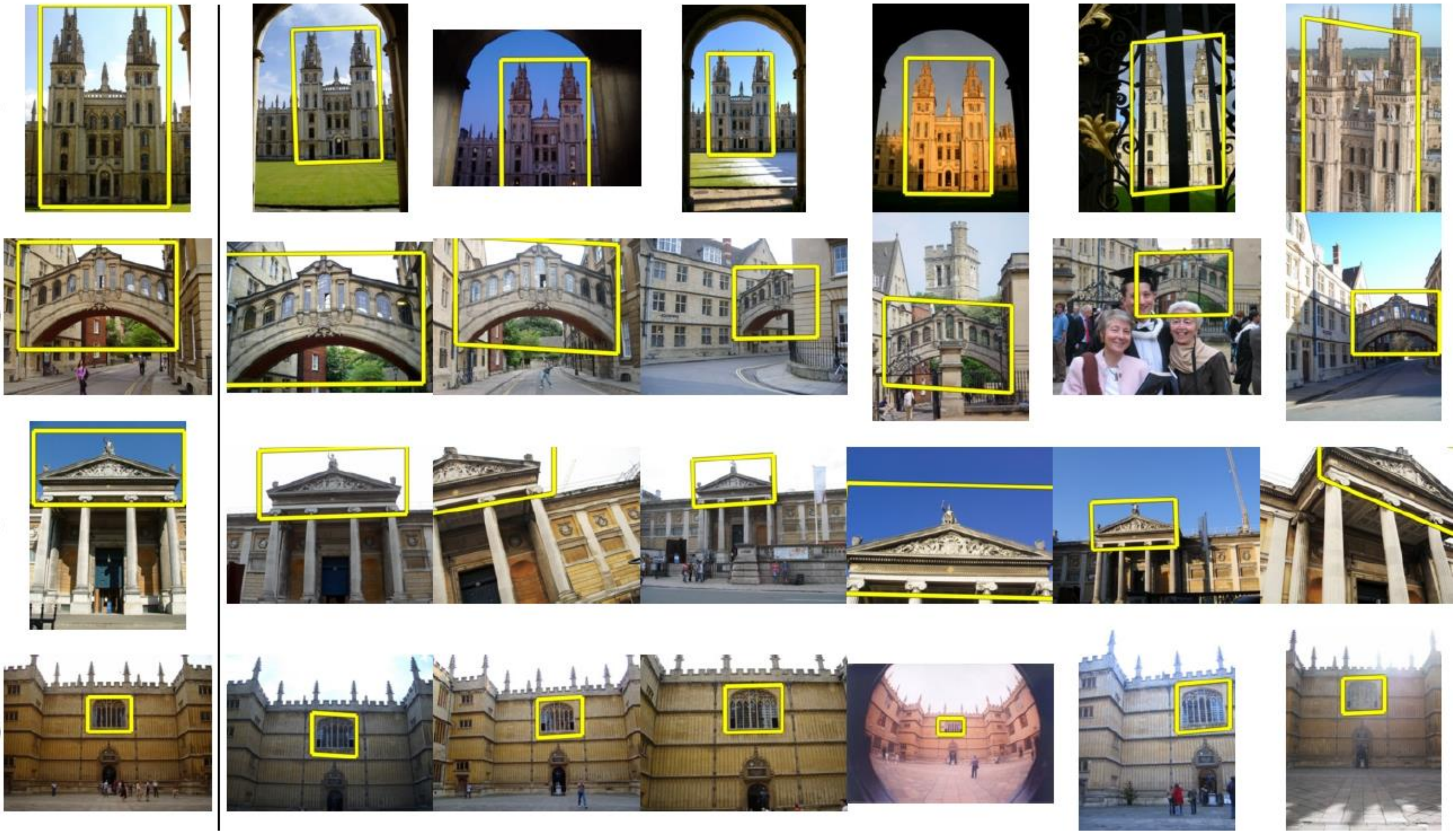


Query region

Retrieved frames

Kristen Grauman

Application: Large-Scale Retrieval



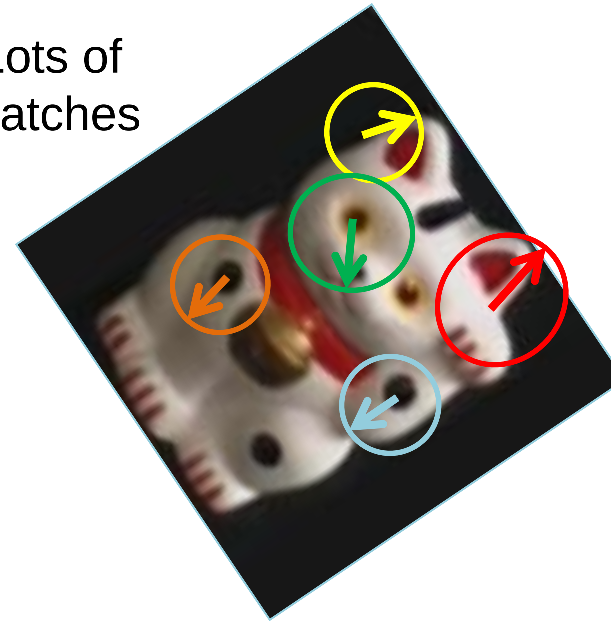
Query   Results from 5k Flickr images (demo available for 100k set)

[Philbin CVPR'07]

Simple idea

See how many keypoints are close to keypoints in each other image

Lots of Matches

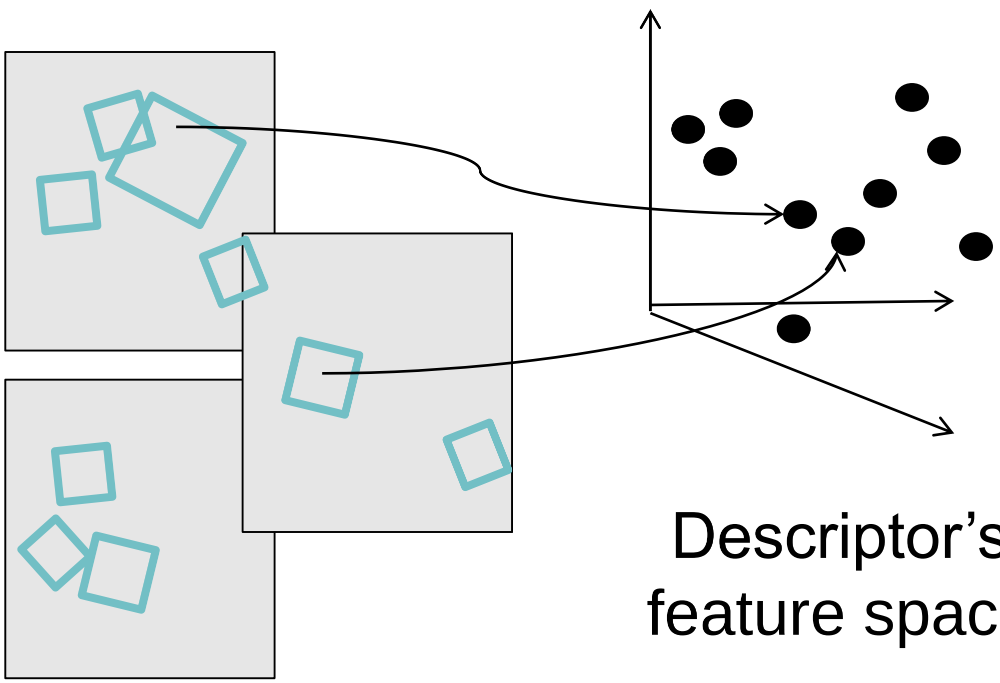


Few or No Matches

But this will be really, really slow!

Indexing local features

- Each patch / region has a descriptor, which is a point in some high-dimensional feature space (e.g., SIFT)

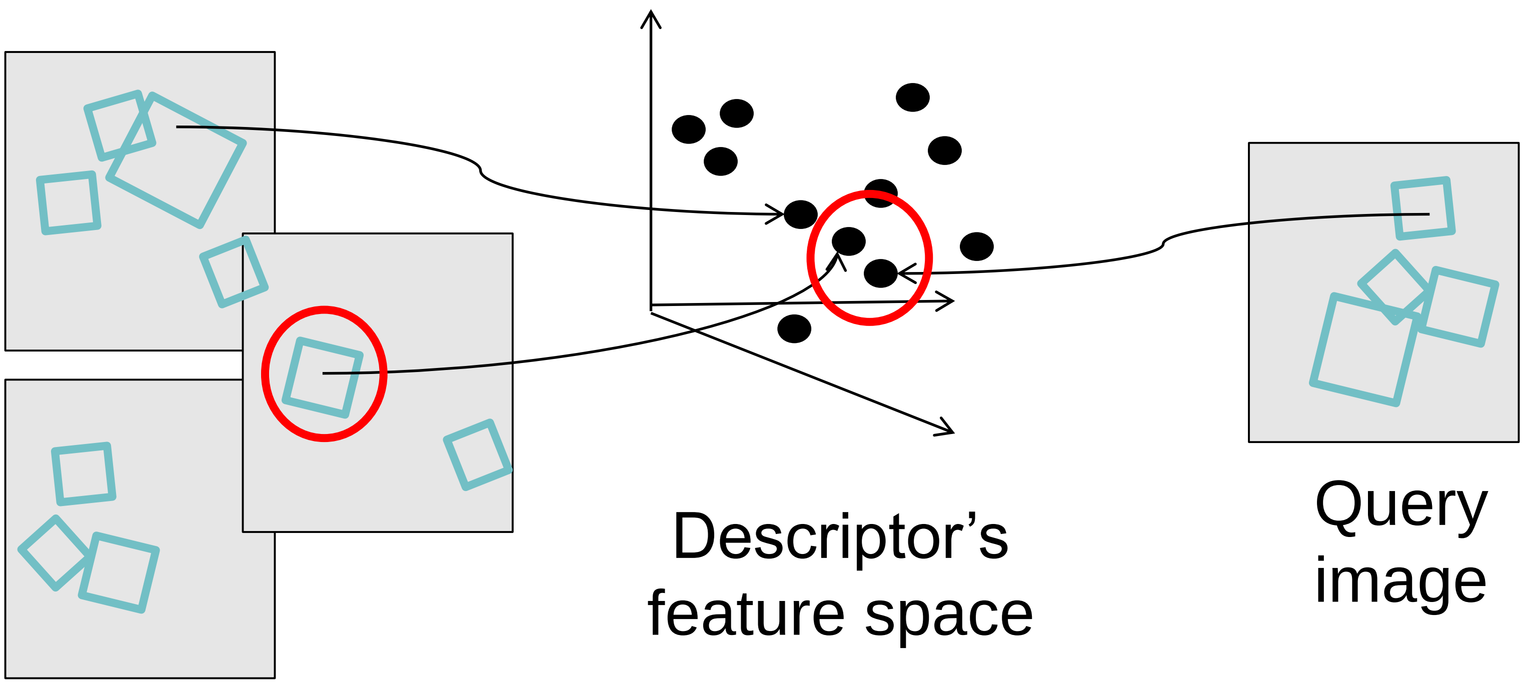


Descriptor's feature space

Kristen Grauman

Indexing local features

- When we see close points in feature space, we have similar descriptors, which indicates similar local content.



Database images

Easily can have millions of features to search!

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Indexing local features: inverted file index

Index

- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index…
- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words".

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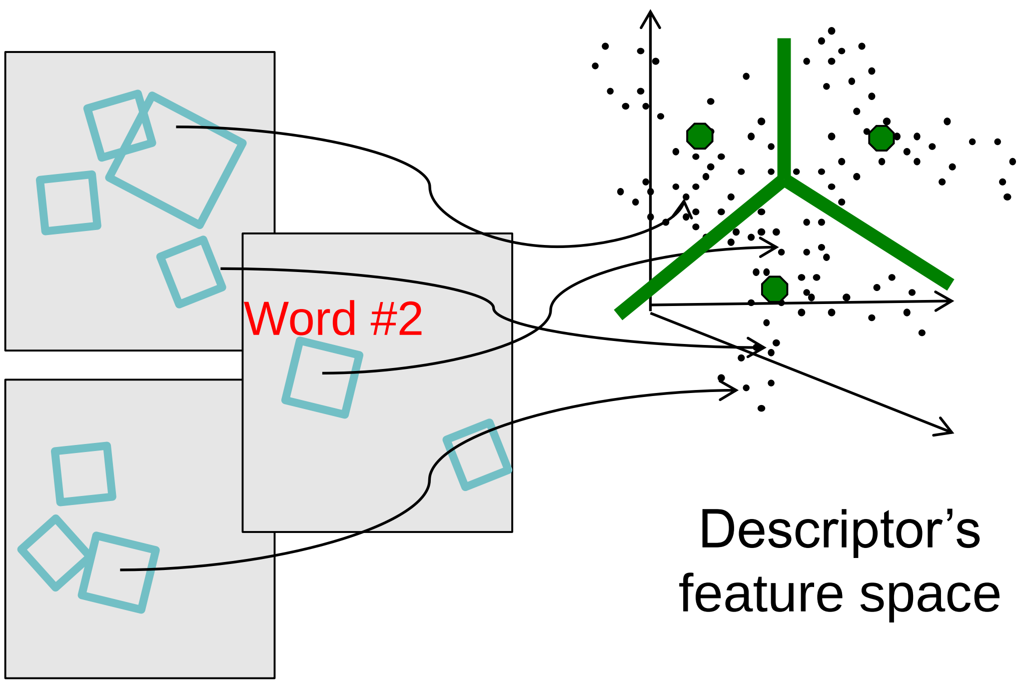
Visual words

- Map high-dimensional descriptors to tokens/words by quantizing the feature space



- Quantize via clustering, let cluster centers be the prototype "words"
- Determine which word to assign to each new image region by finding the closest cluster center.

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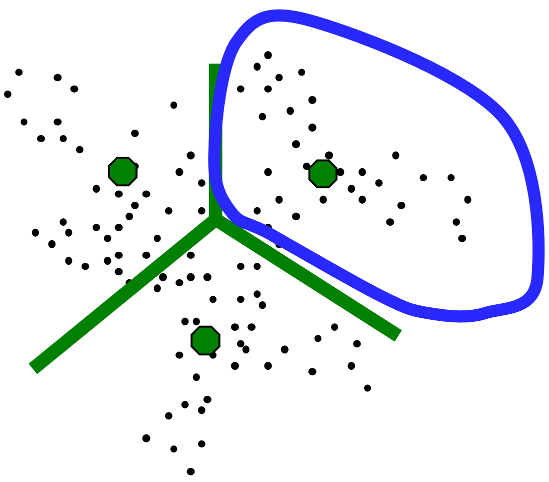
Visual words

- Example: each group of patches belongs to the same visual word



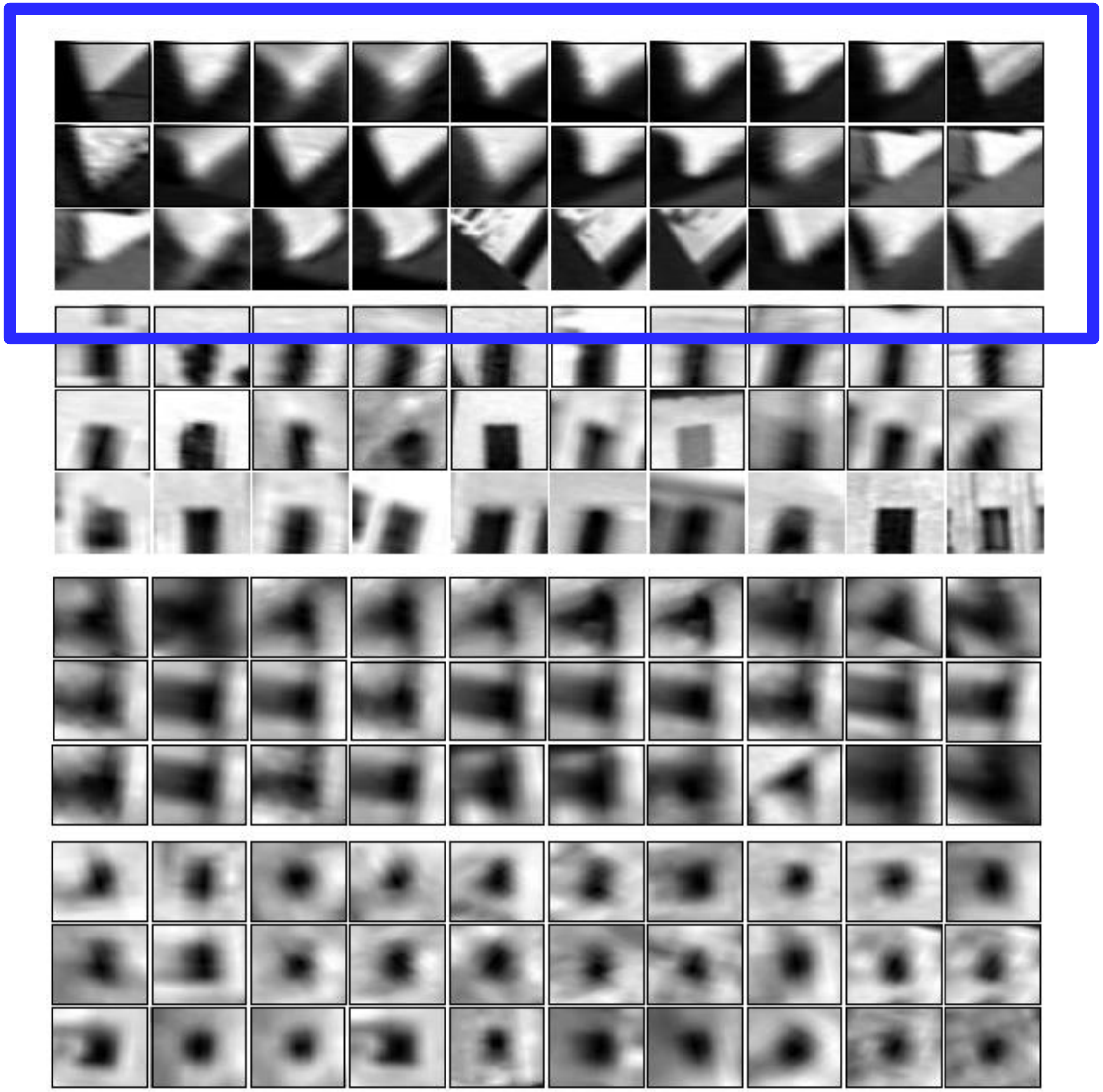


Figure from Sivic & Zisserman, ICCV 2003

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Visual vocabulary formation

Issues:

- Vocabulary size, number of words
- Sampling strategy: where to extract features?
- Clustering / quantization algorithm
- Unsupervised vs. supervised
- What corpus provides features (universal vocabulary?)

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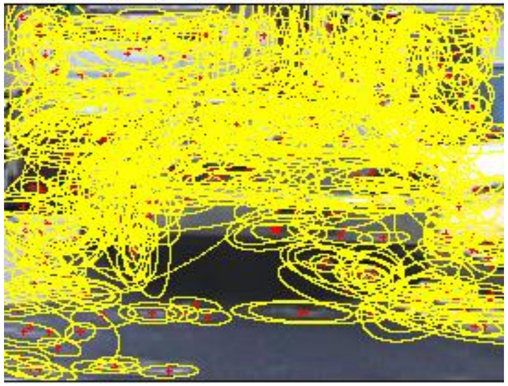
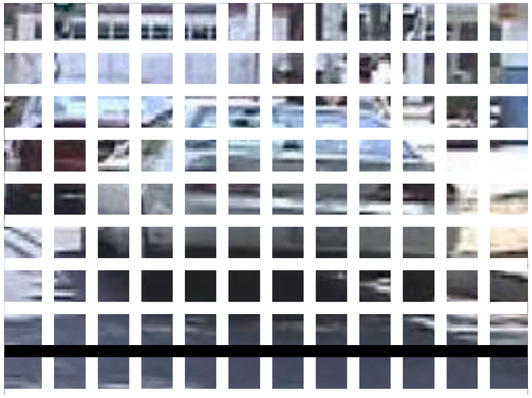
Sampling strategies

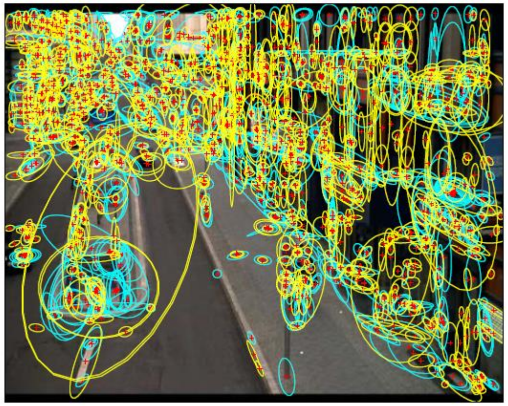


Sparse, at interest points



Dense, uniformly

Randomly



Multiple interest operators

- To find specific, textured objects, sparse sampling from interest points often more reliable.
- Multiple complementary interest operators offer more image coverage.
- For object categorization, dense sampling offers better coverage.

[See Nowak, Jurie & Triggs, ECCV 2006]

Image credits: F-F. Li, E. Nowak, J. Sivic

Inverted file index

Database images

Image #1

Image #2

Image #3

Word #	Image #
1	3
2 …	
7	1, 2
8	3
9	
10 …	
91	2

…

- Database images are loaded into the index mapping words to image numbers

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Inverted file index

New query image

Word #	Image #
1	3
2 ...	
7	1, 2
8	3
9	
10 ...	
91	2

...

- New query image is mapped to indices of database images that share a word.

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Inverted file index

- Key requirement for inverted file index to be efficient: sparsity
- If most pages/images contain most words then you're no better off than exhaustive search.
  - Exhaustive search would mean comparing the word distribution of a query versus every page.

Instance recognition: remaining issues

- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
- Is having the same set of visual words enough to identify the object/scene? How to verify spatial agreement?
- How to score the retrieval results?

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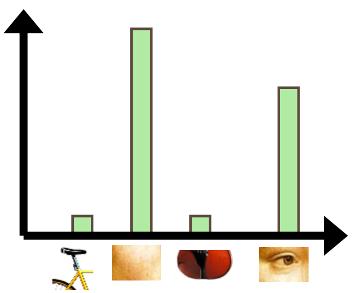
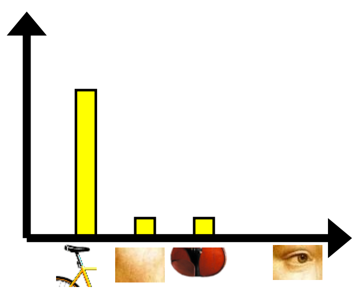
Comparing bags of words

- Rank frames by normalized scalar product between their (possibly weighted) occurrence counts---*nearest neighbor* search for similar images.

[1 8 1 4]

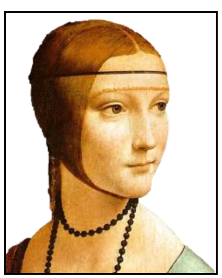


[5 1 1 0]

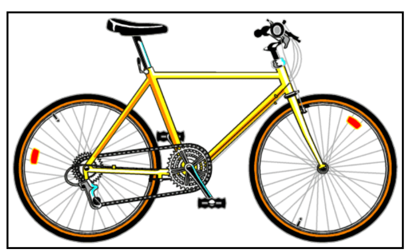


$$sim(d_j, q) = \frac{\langle d_j, q \rangle}{\|d_j\| \|q\|}$$

$$= \frac{\sum_{i=1}^{V} d_j(i) * q(i)}{\sqrt{\sum_{i=1}^{V} d_j(i)^2} * \sqrt{\sum_{i=1}^{V} q(i}}$$



$\vec{d}_j$



$\vec{q}$

for vocabulary of *V* words

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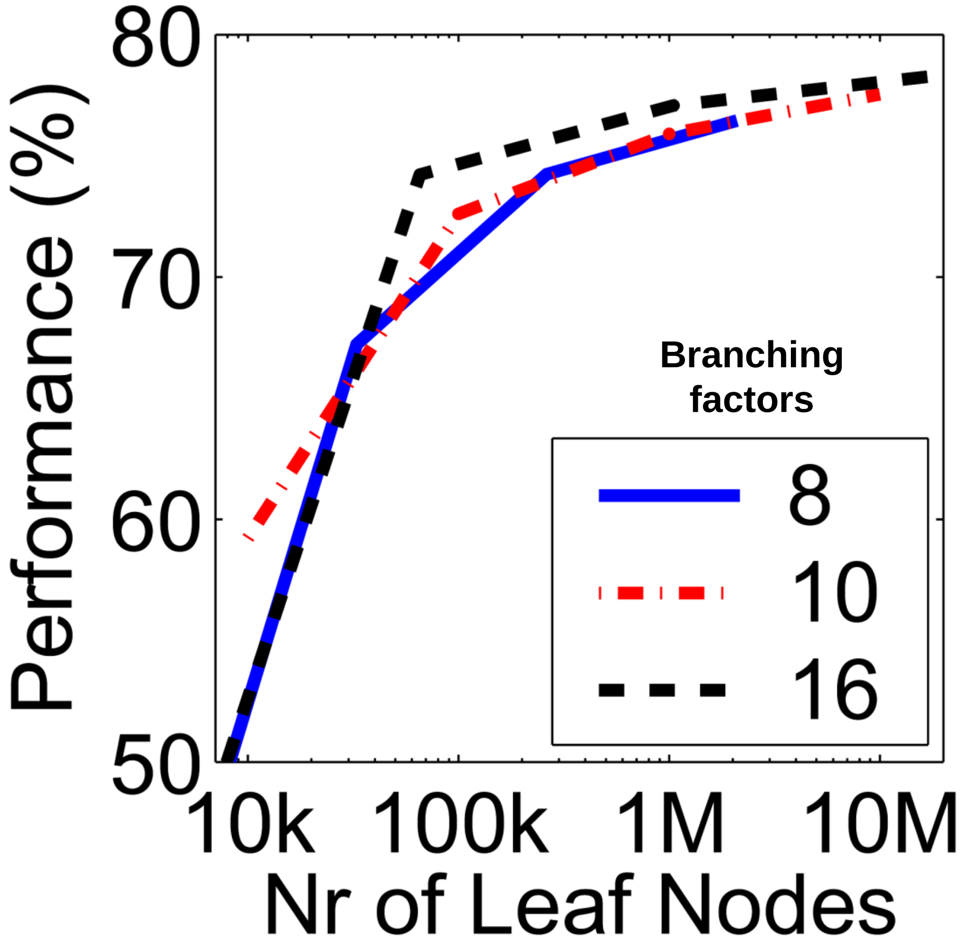
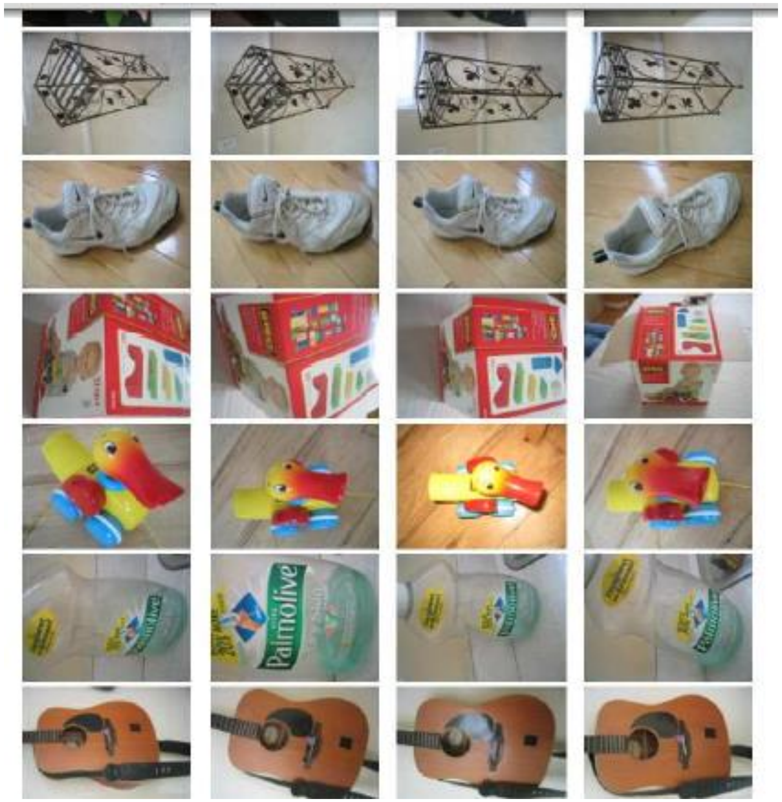
Vocabulary size



Influence on performance, sparsity

Results for recognition task with 6347 images



Nister & Stewenius, CVPR 2006

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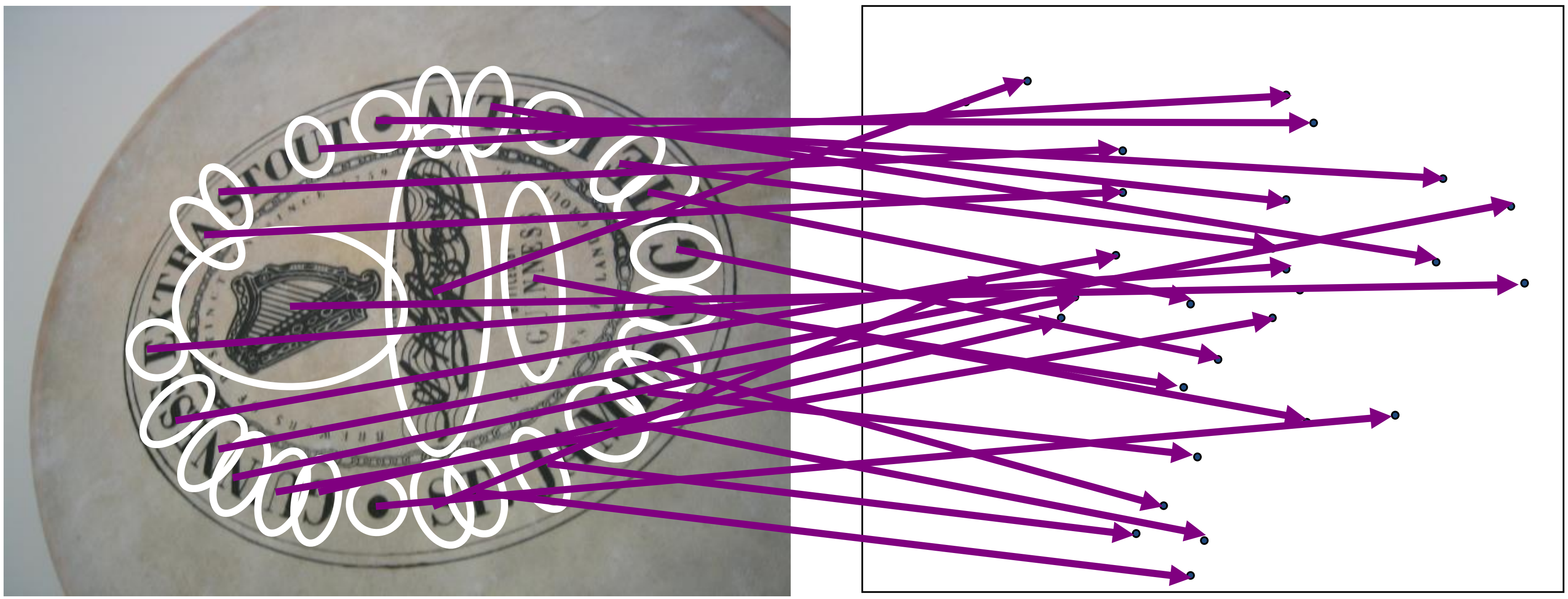
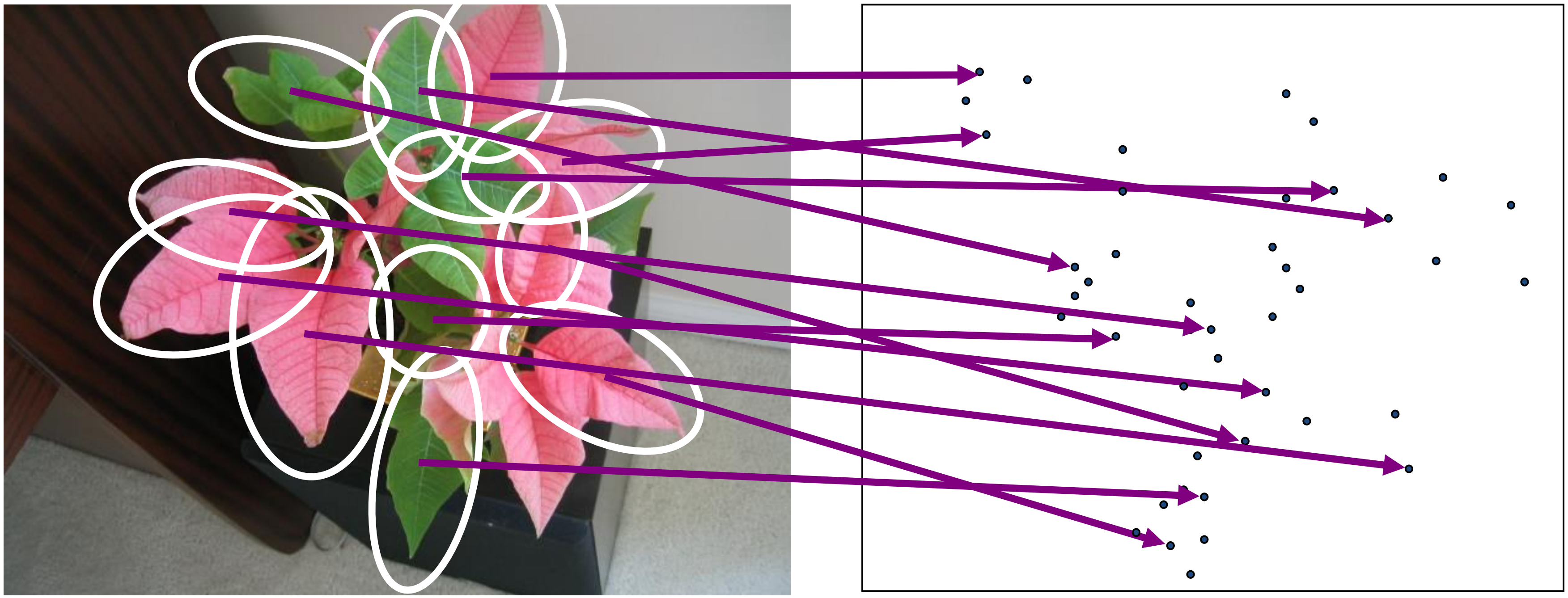
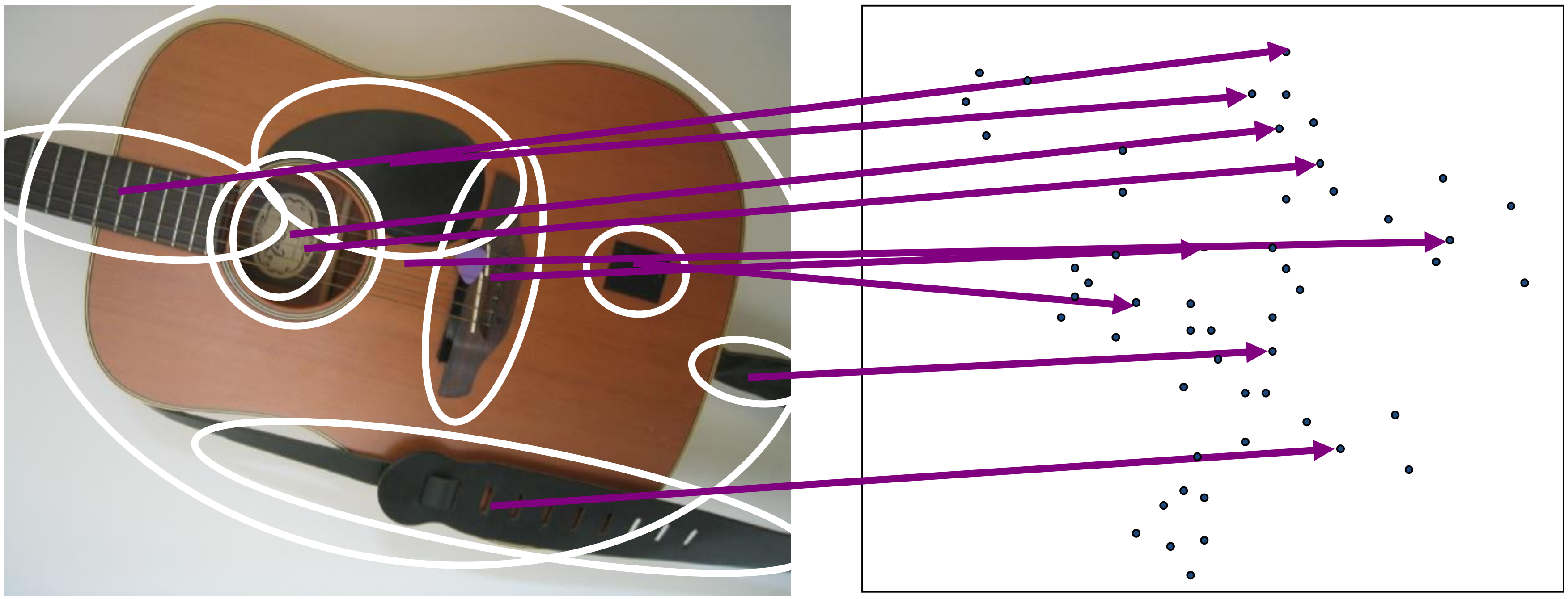
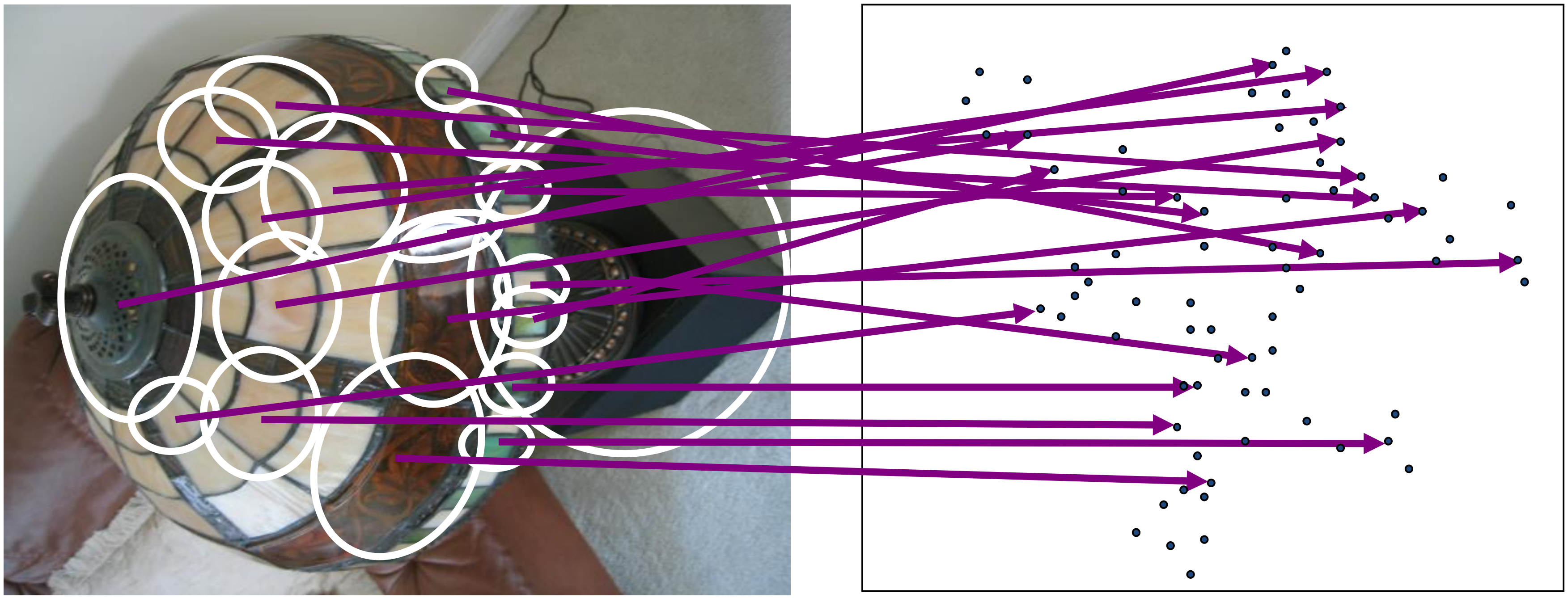
Recognition with K-tree

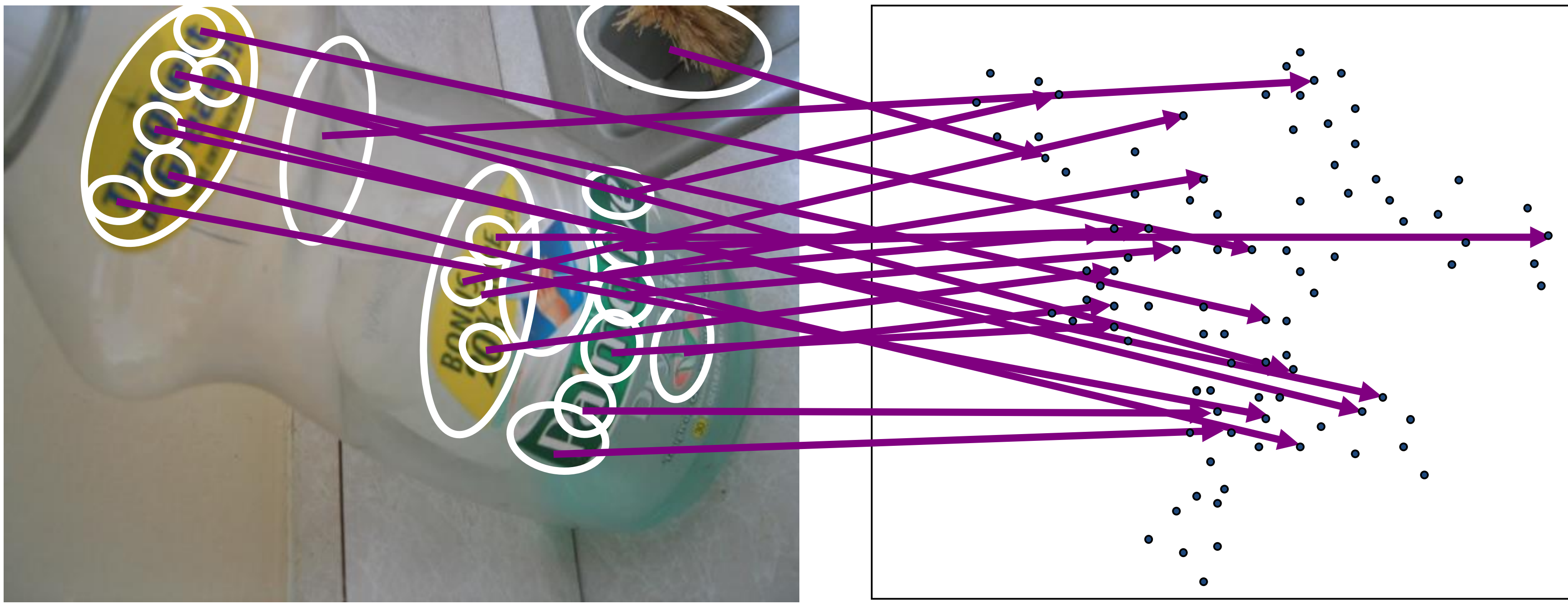
Following slides by David Nister (CVPR 2006)

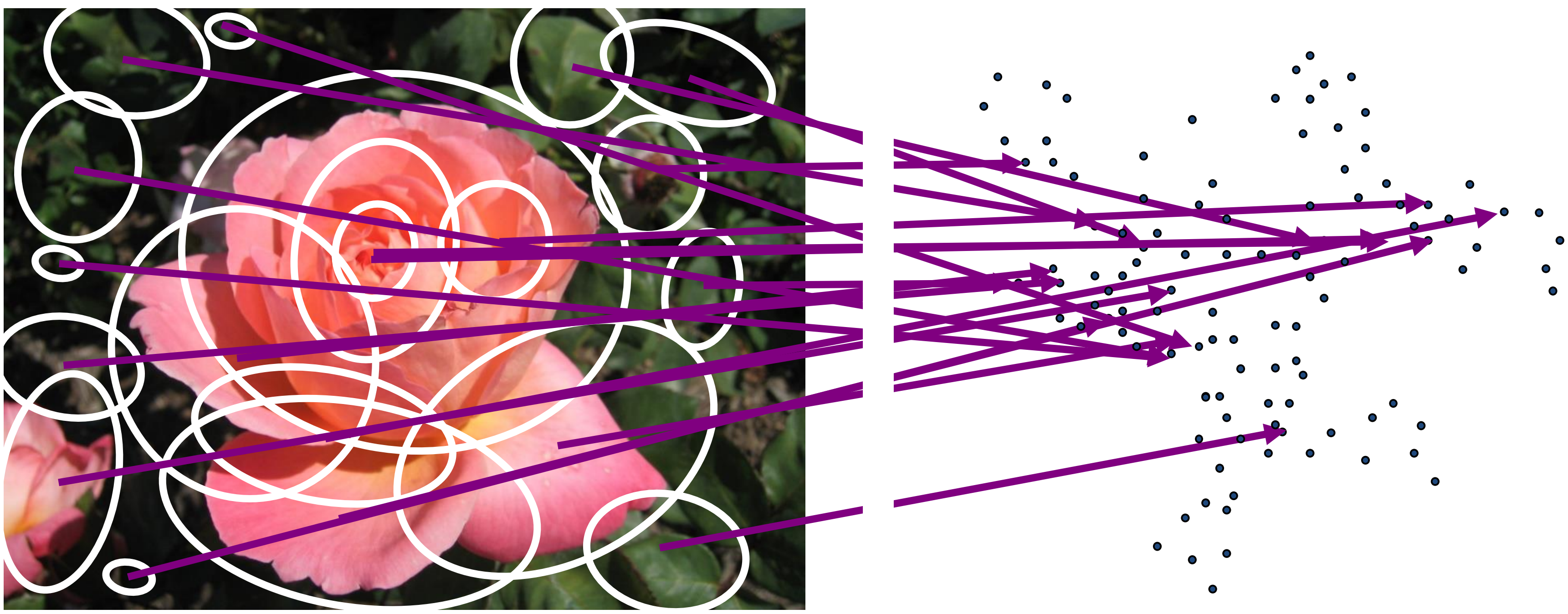


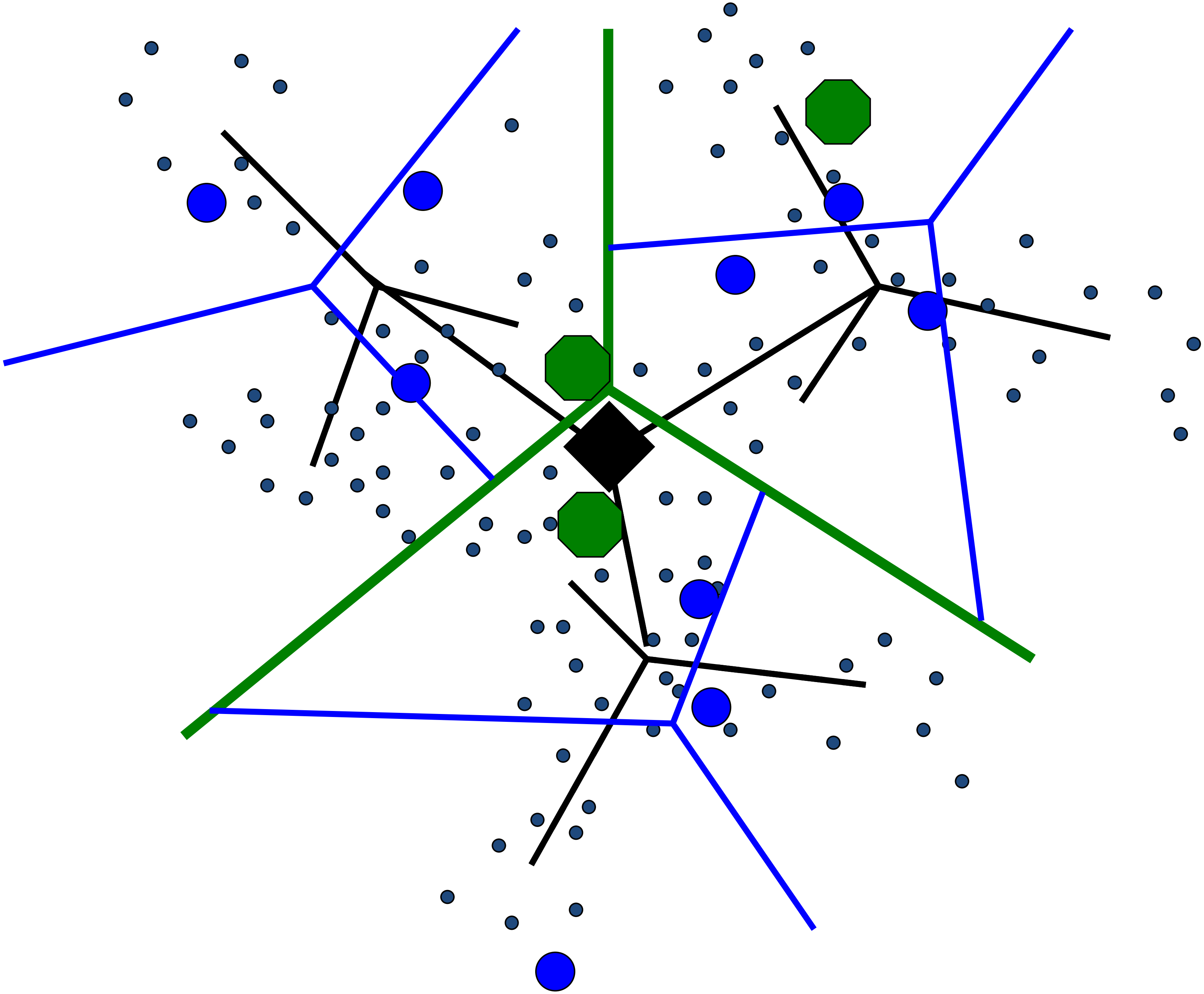


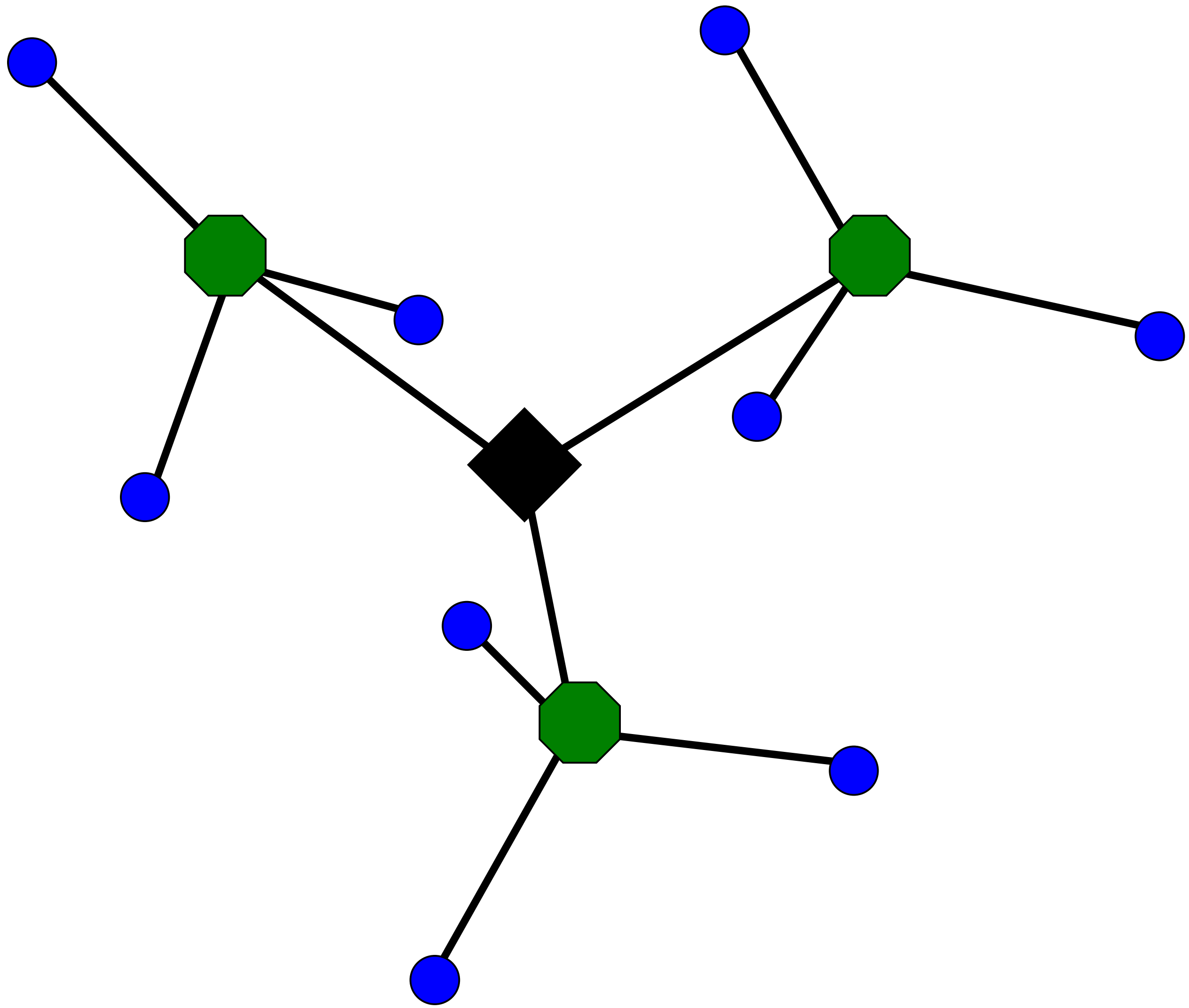


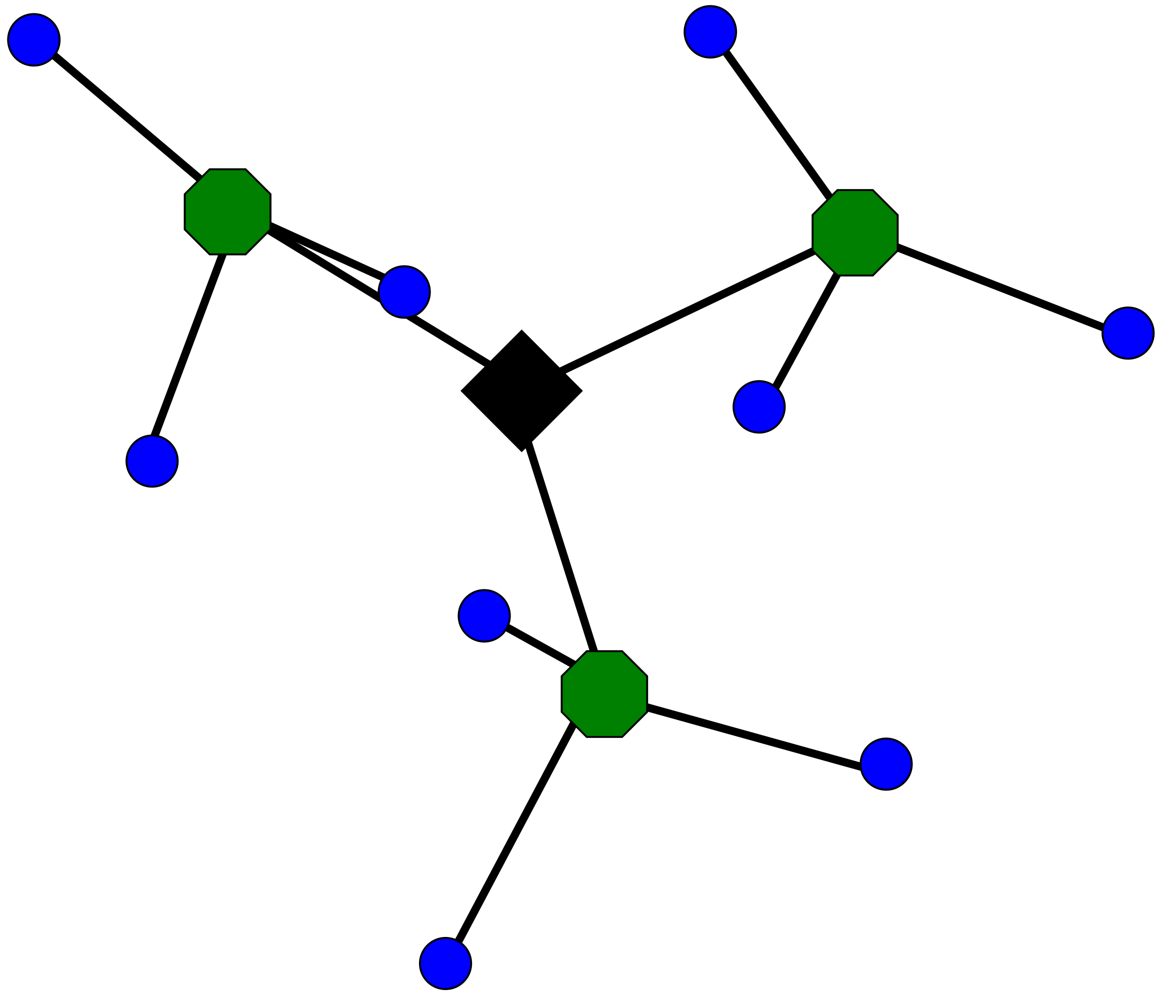


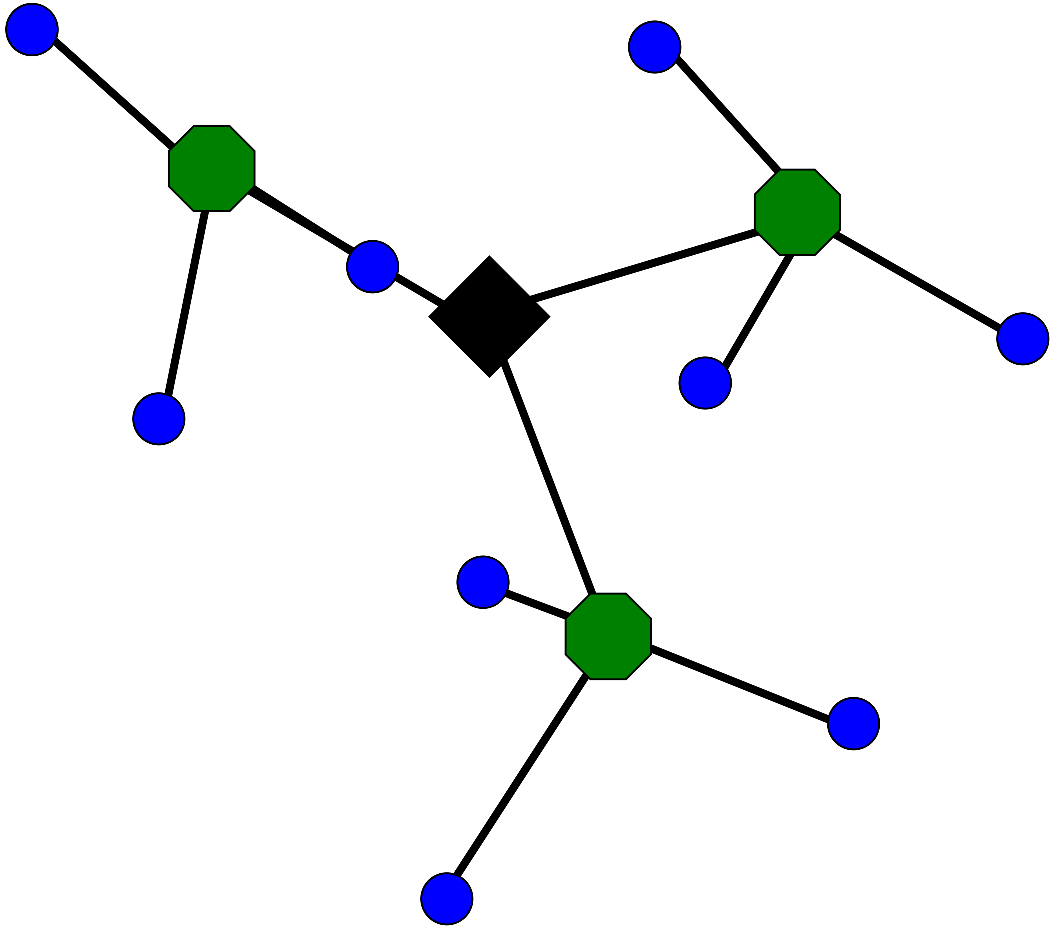


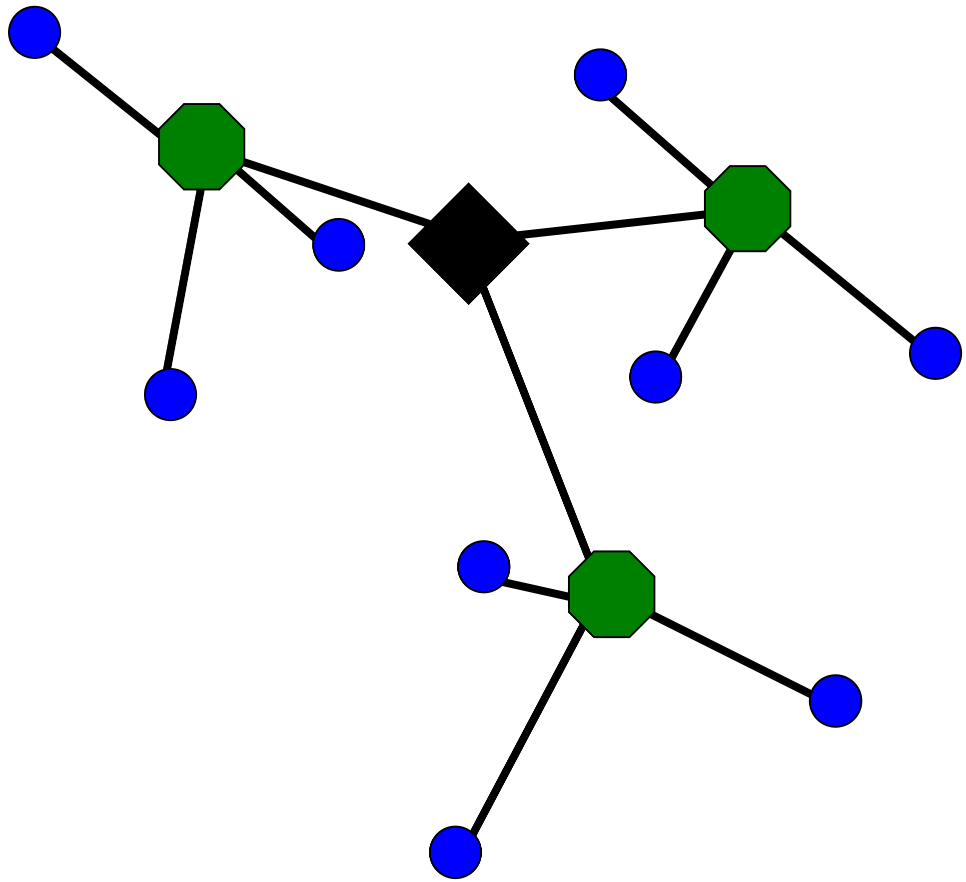


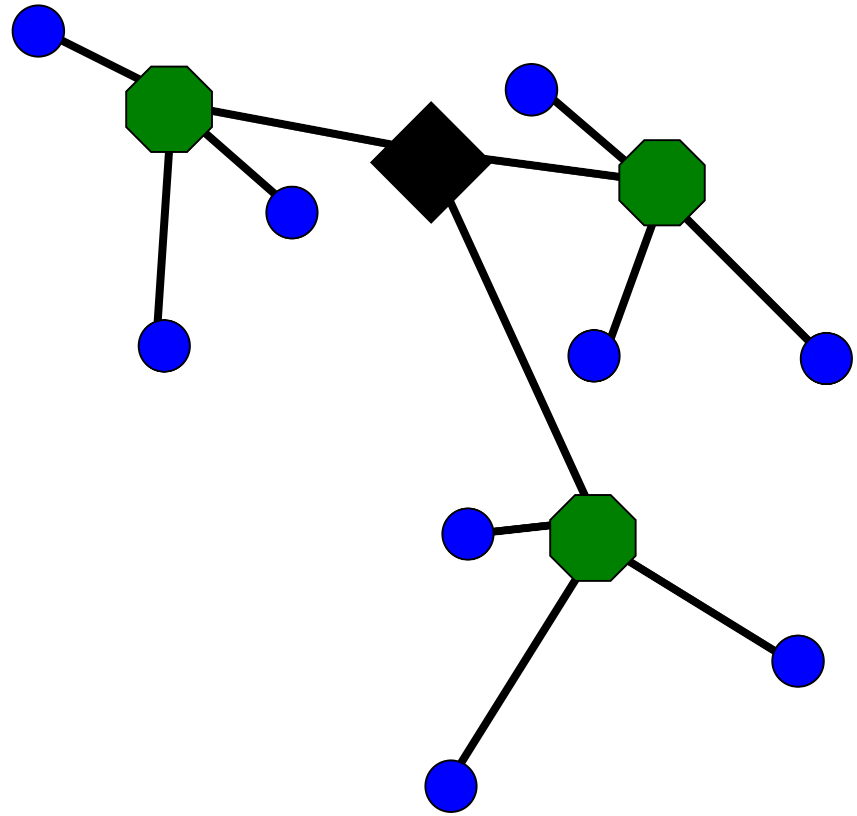


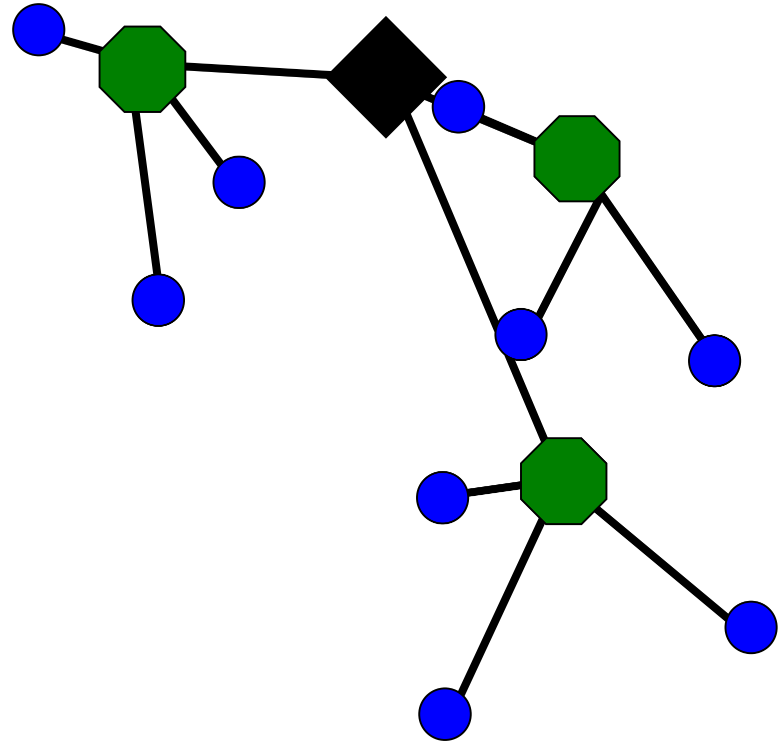


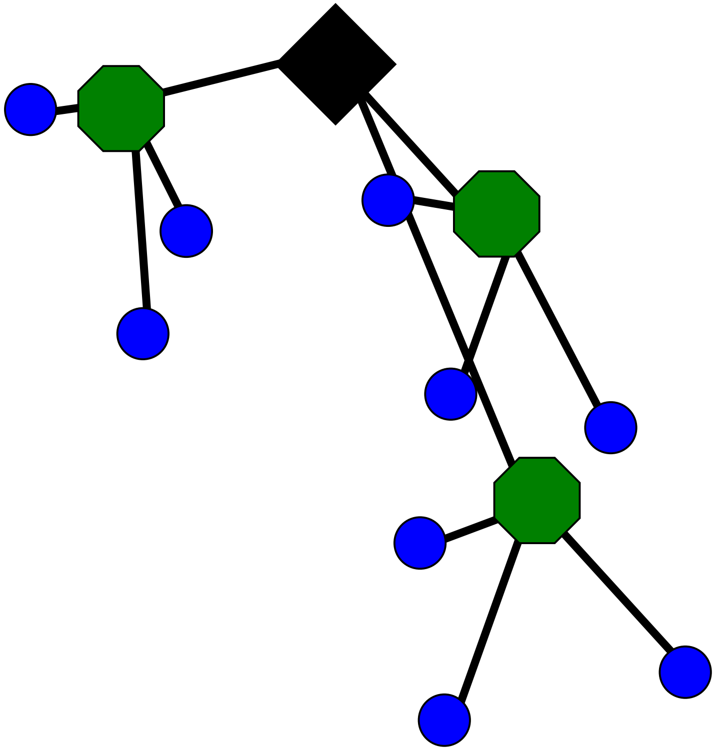


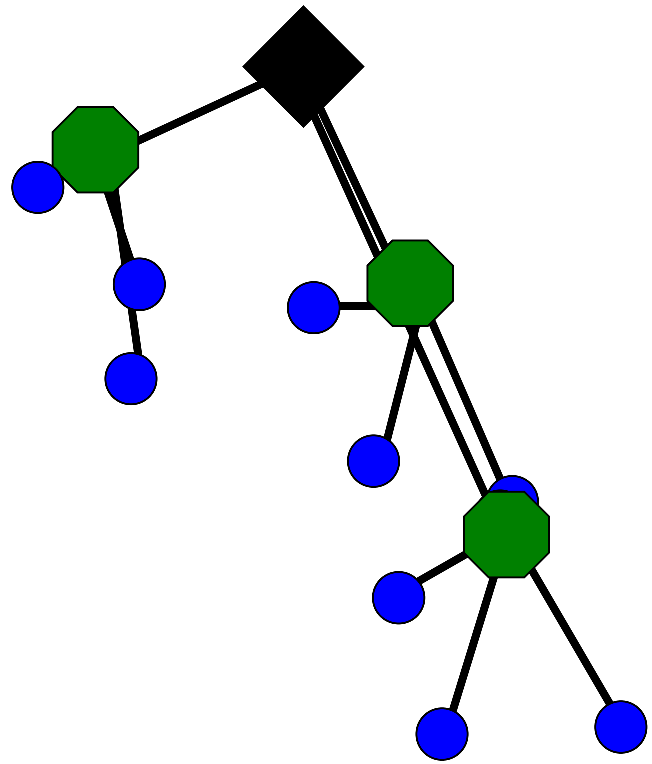


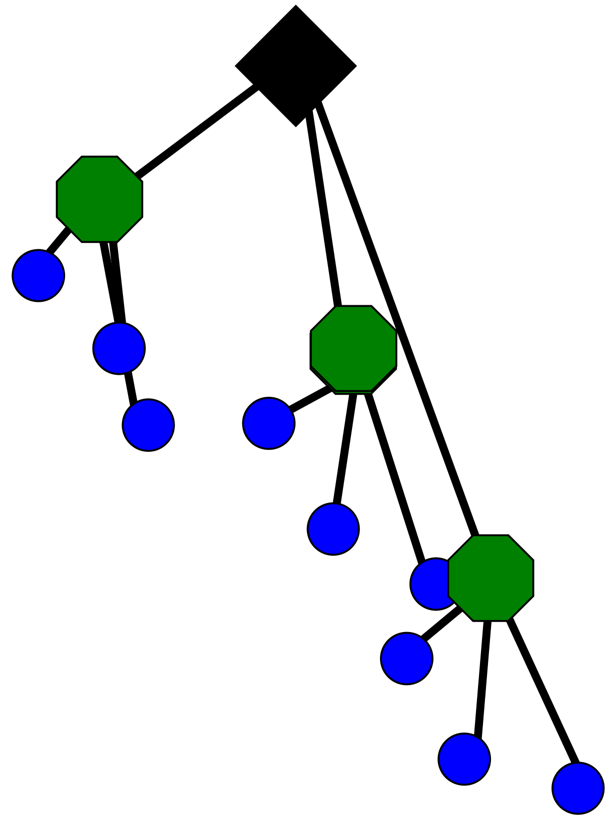


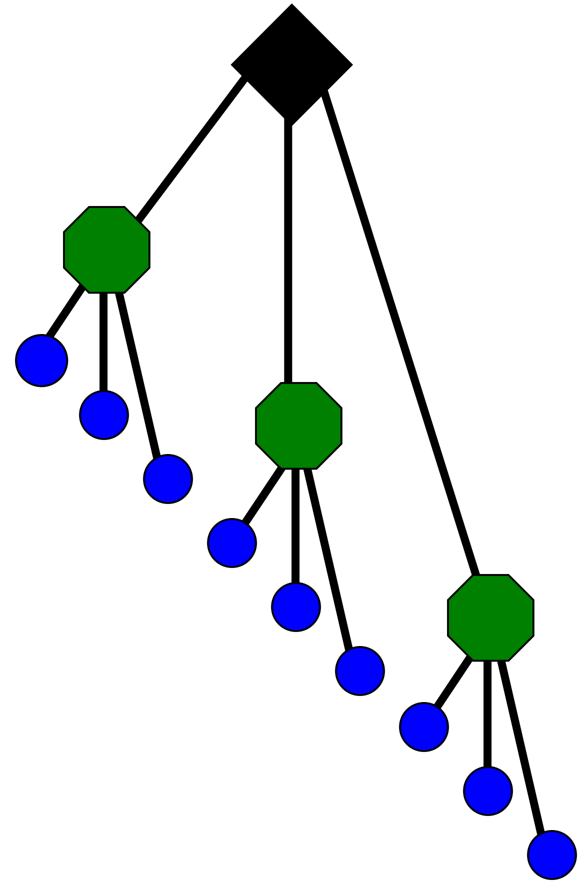


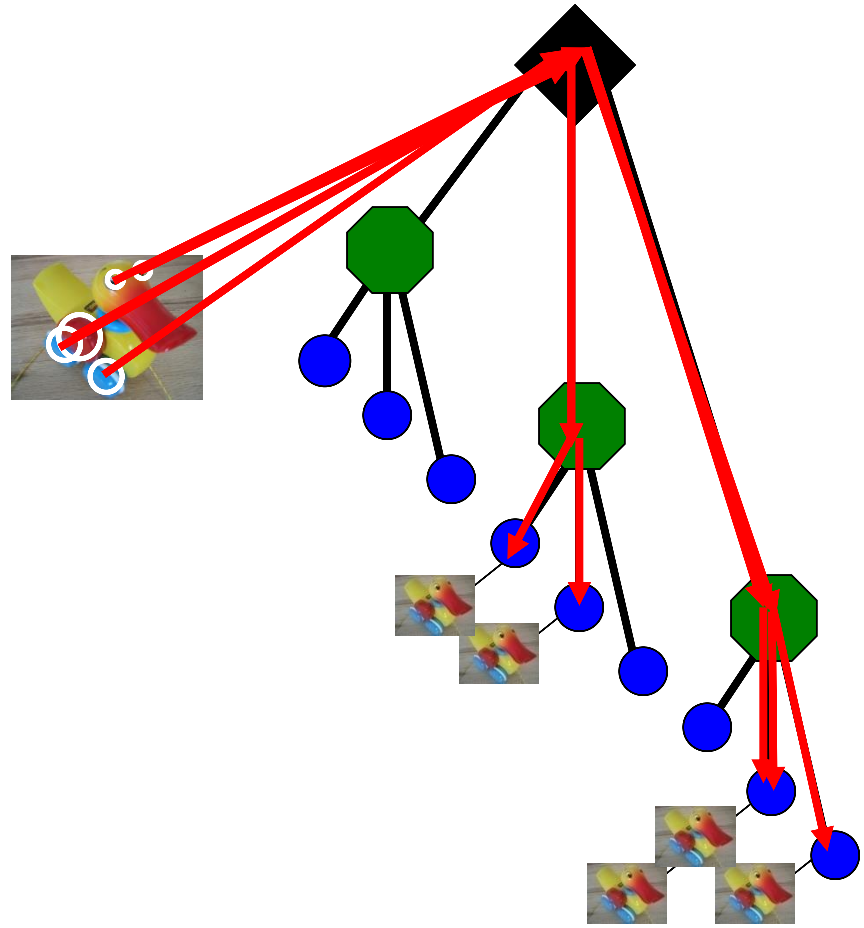


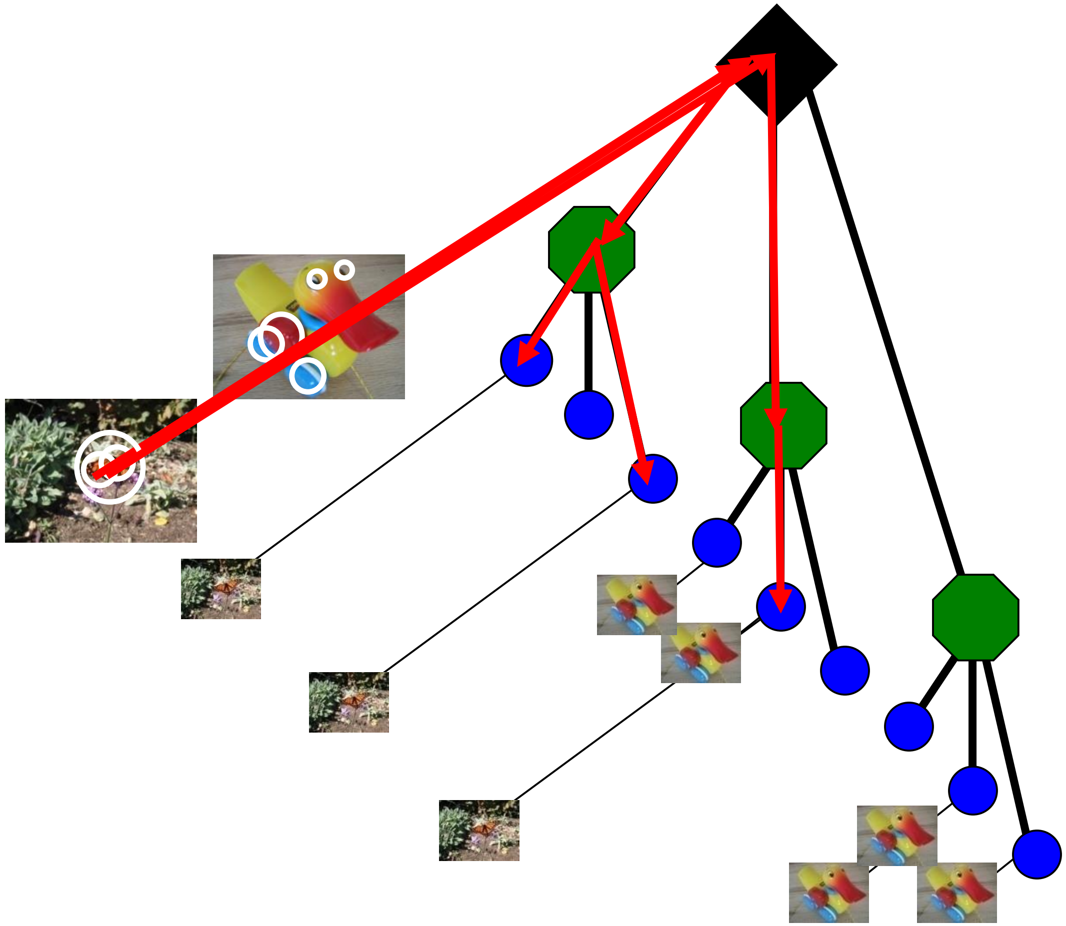


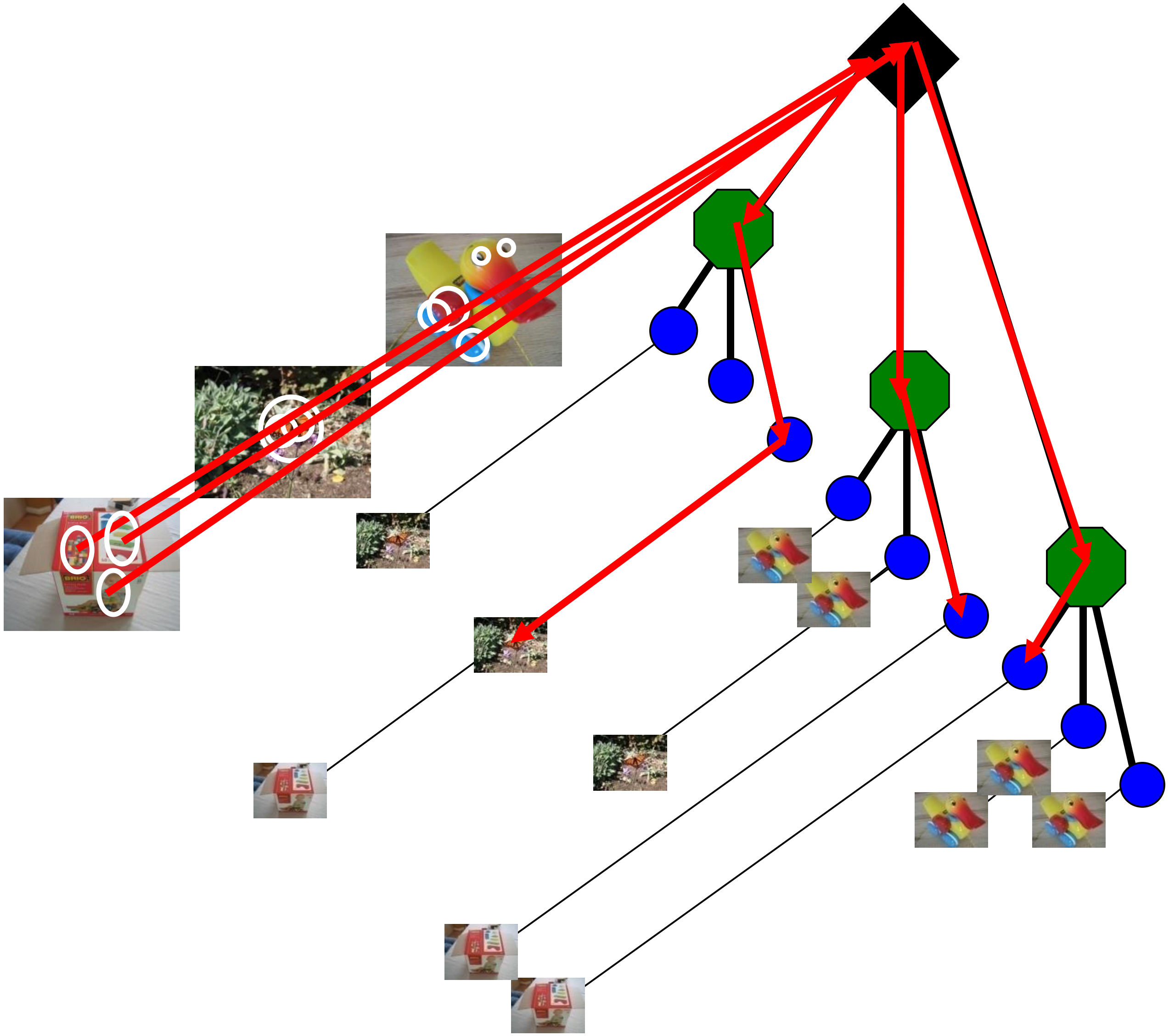


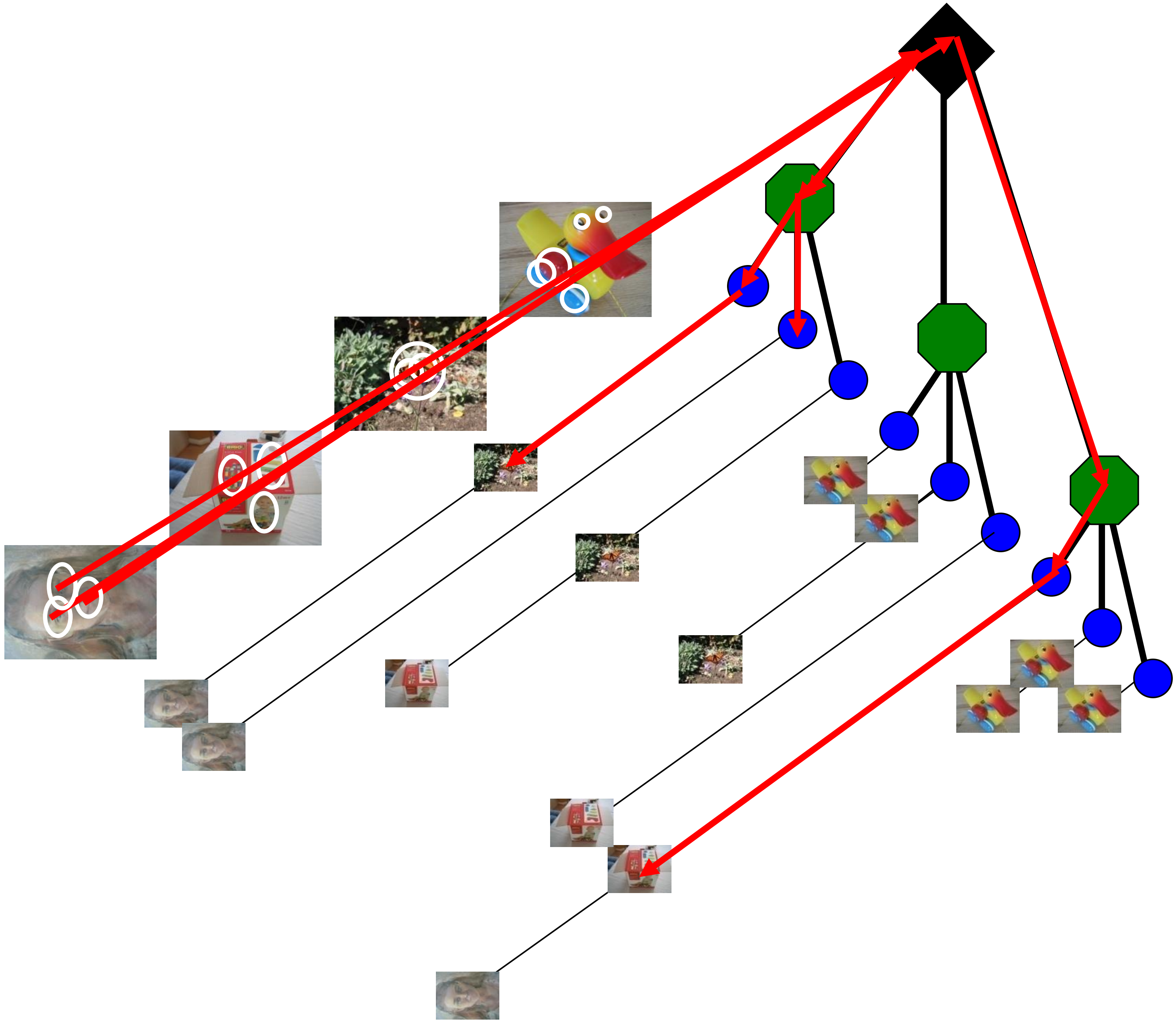


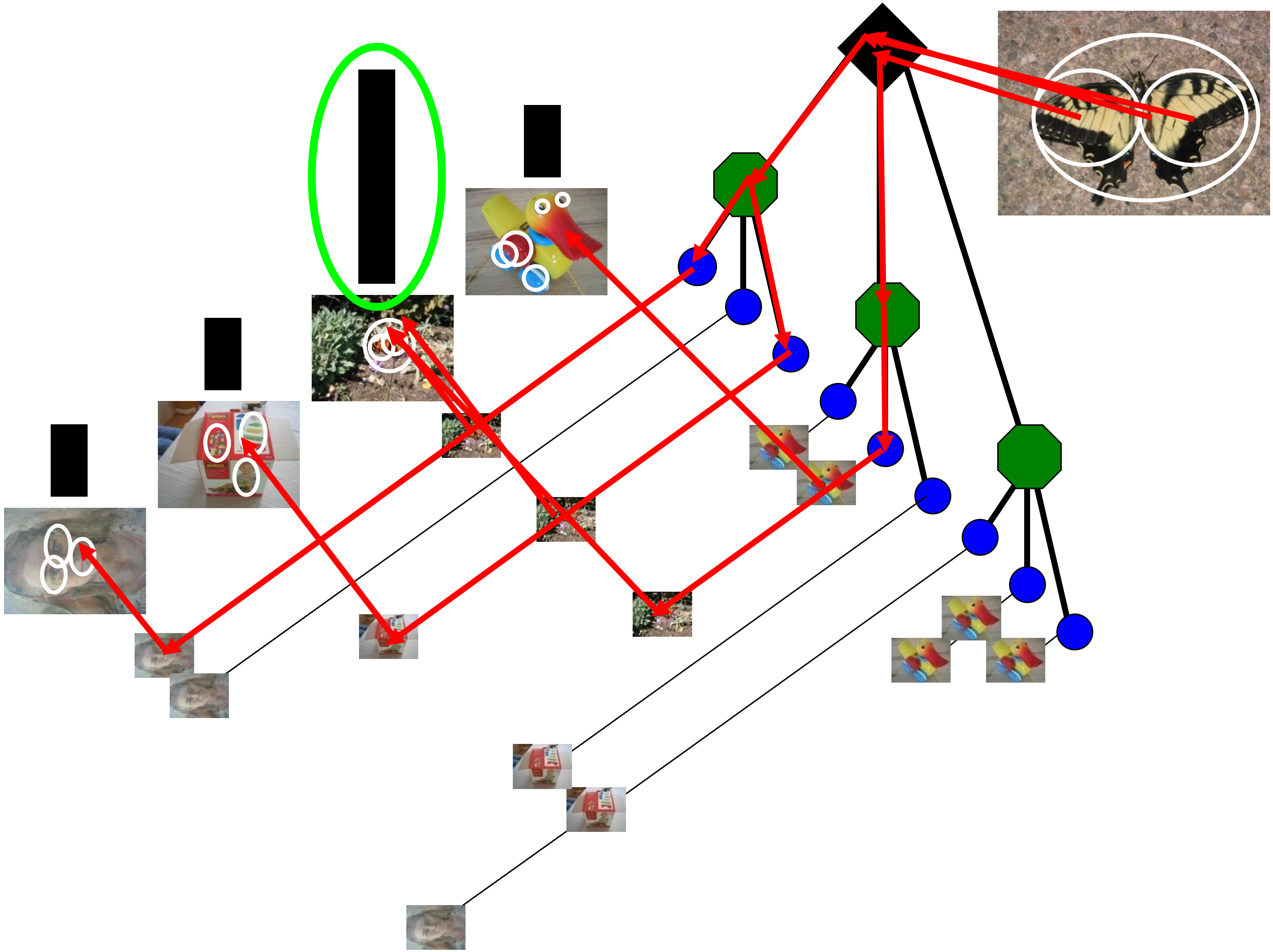












Vocabulary trees: complexity

Number of words given tree parameters: branching factor and number of levels

branching_factor^number_of_levels

Word assignment cost vs. flat vocabulary

O(k) for flat

$O(\log_{branching\_factor}(k) * branching\_factor)$

Is this like a kd-tree?

Yes, but with better partitioning and defeatist search.

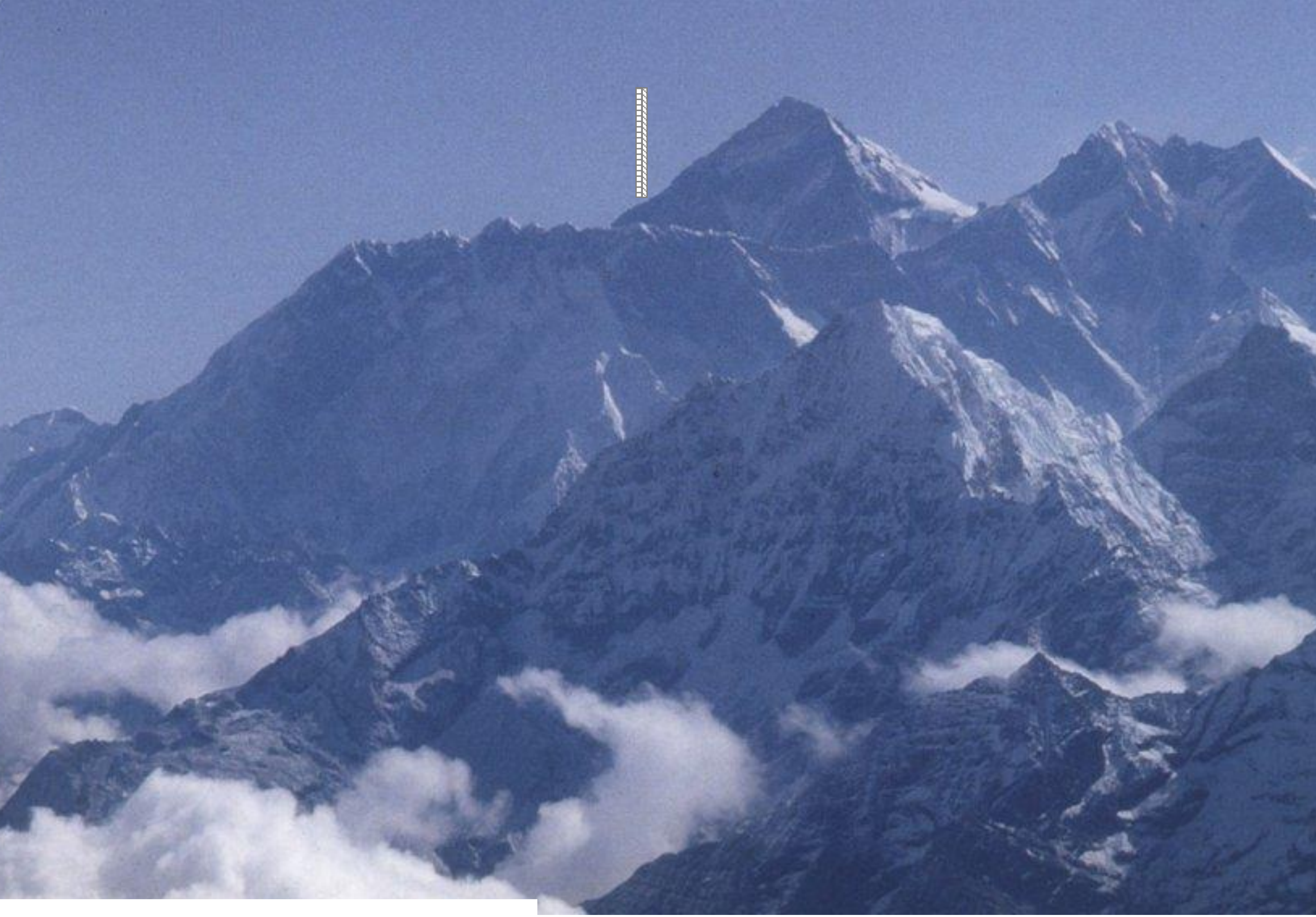
This hierarchical data structure is lossy – you might not find your true nearest cluster.

110,000,000 Images in 5.8 Seconds

Slide Credit: Nister

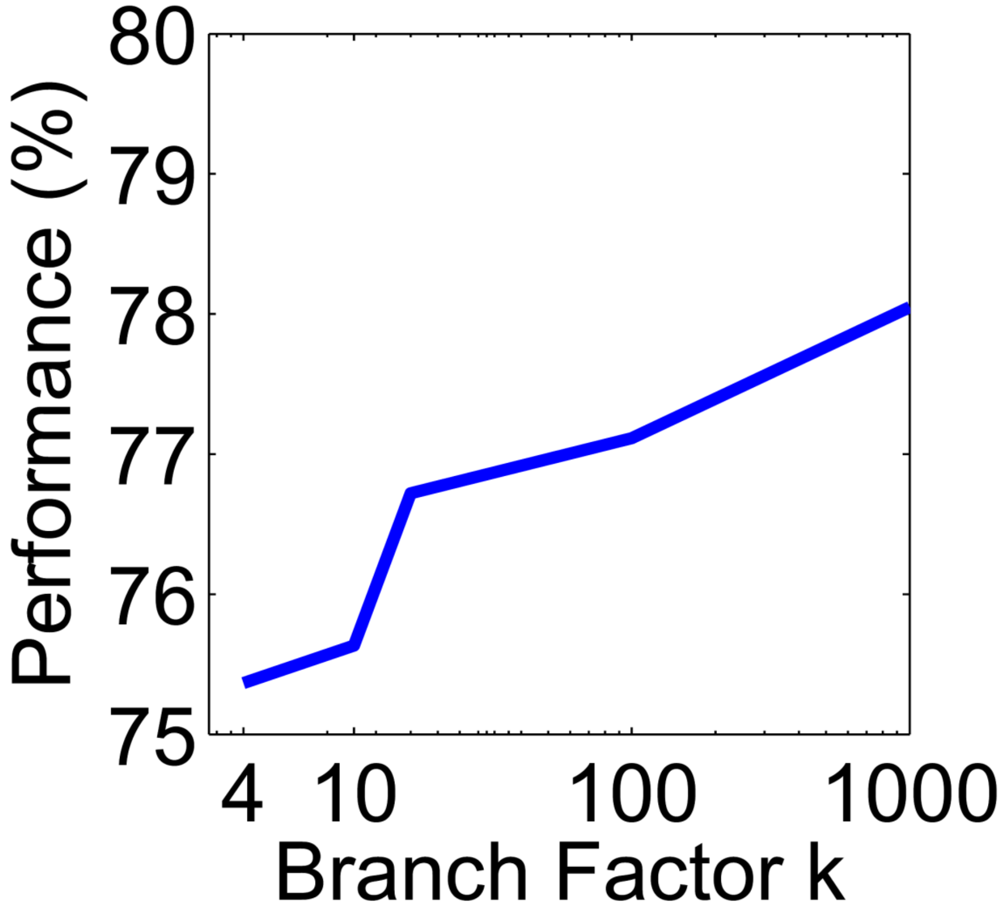
Slide Credit: Nister

Slide Credit: Nister



Slide Credit: Nister

Higher branch factor works better (but slower)



Visual words/bags of words

+ flexible to geometry / deformations / viewpoint
+ compact summary of image content
+ provides fixed dimensional vector representation for sets
+ very good results in practice

- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear
- basic model ignores geometry – must verify afterwards, or encode via features

Kristen Grauman

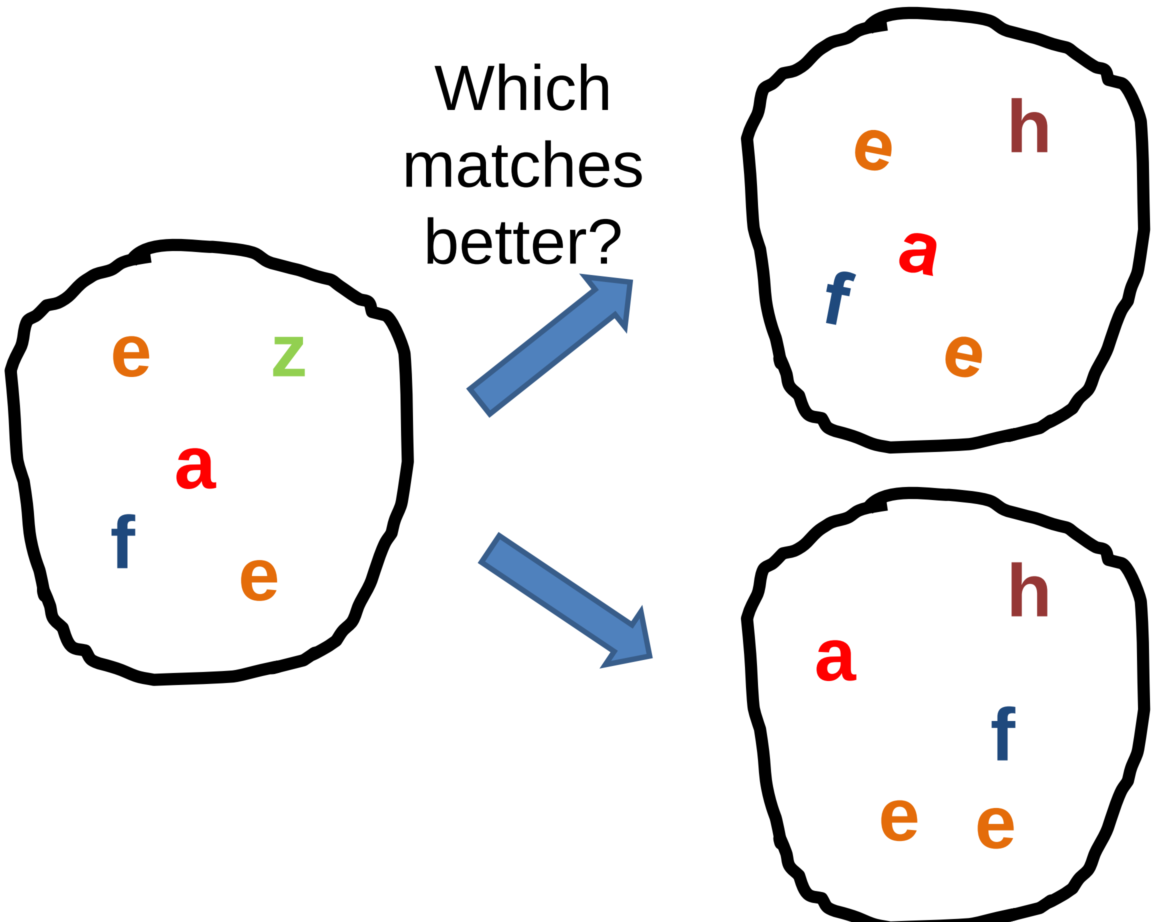
Instance recognition: remaining issues

- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
- Is having the same set of visual words enough to identify the object/scene? How to verify spatial agreement?
- How to score the retrieval results?

Kristen Grauman

Can we be more accurate?

So far, we treat each image as containing a "bag of words", with no spatial information



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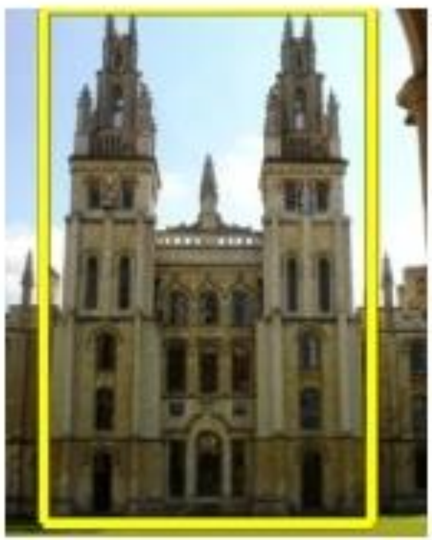


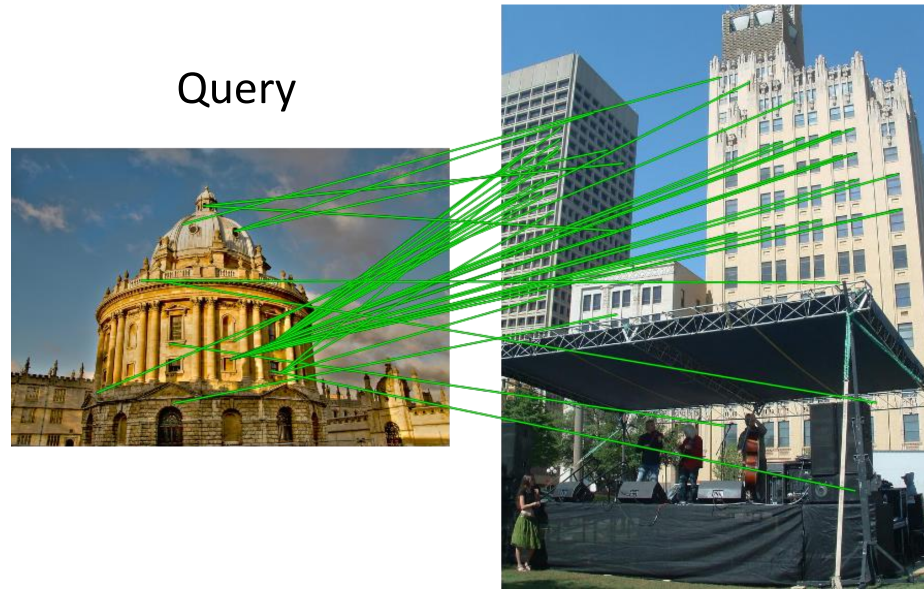

Real objects have consistent geometry

Spatial Verification

Query

DB image with high BoW similarity

Query



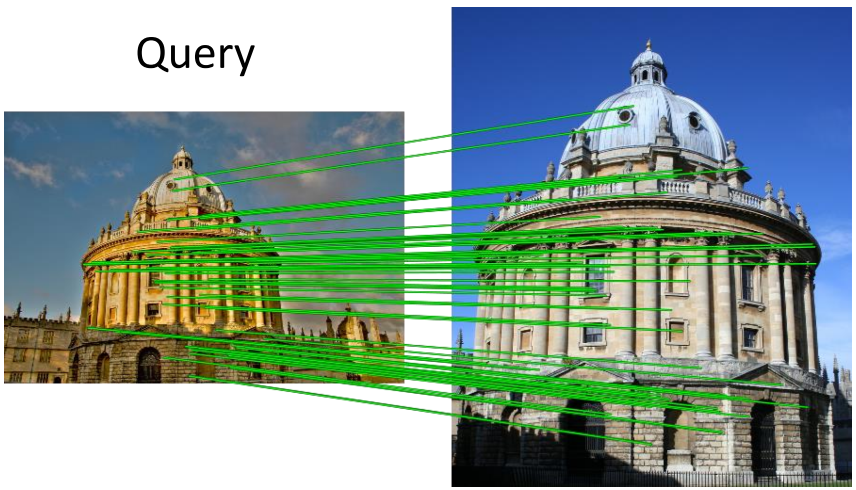
DB image with high BoW similarity

Both image pairs have many visual words in common.

Slide credit: Ondrej Chum

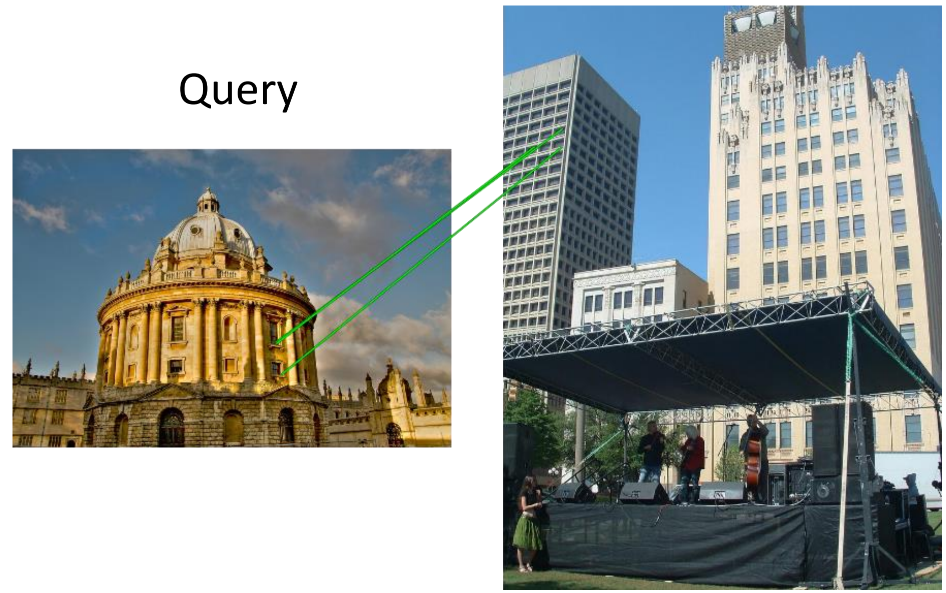
Spatial Verification

Query



DB image with high BoW similarity

Query



DB image with high BoW similarity

Only some of the matches are mutually consistent

Slide credit: Ondrej Chum

Spatial Verification: two basic strategies

- RANSAC
  - Typically sort by BoW similarity as initial filter
  - Verify by checking support (inliers) for possible transformations
    - e.g., “success” if find a transformation with > N inlier correspondences

- Generalized Hough Transform
  - Let each matched feature cast a vote on location, scale, orientation of the model object
  - Verify parameters with enough votes

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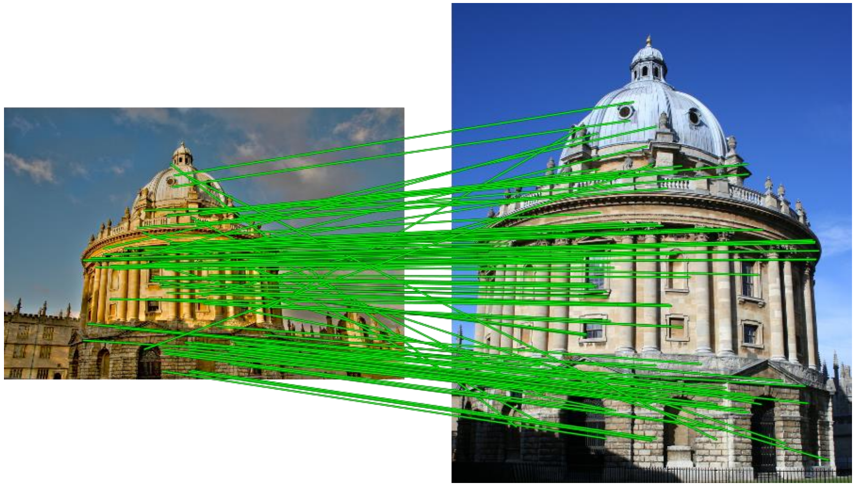
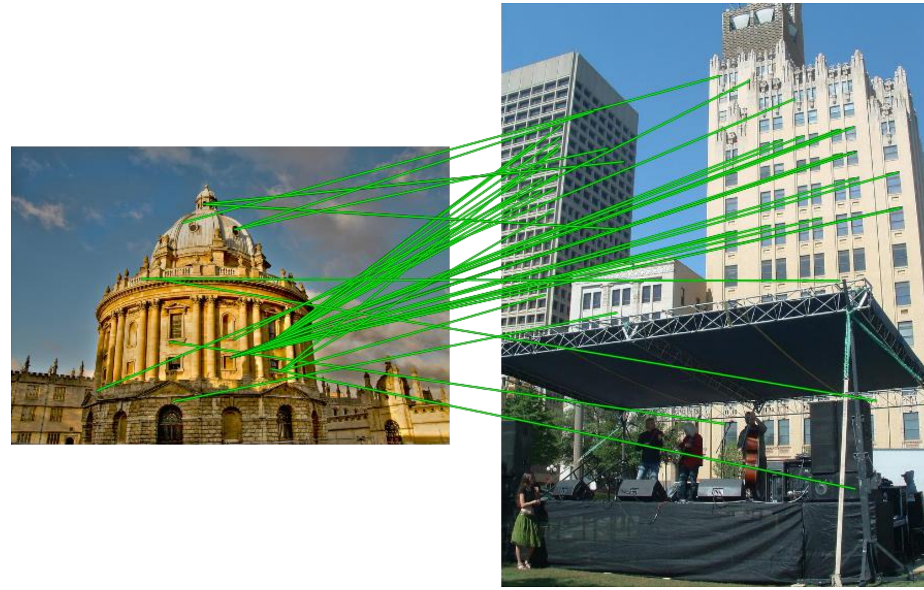
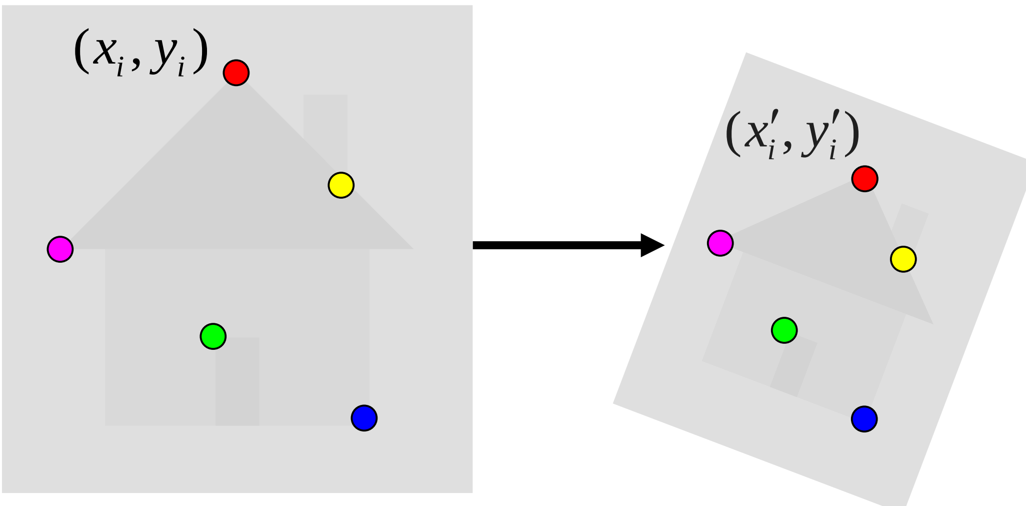
RANSAC verification





Recall: Fitting an affine transformation

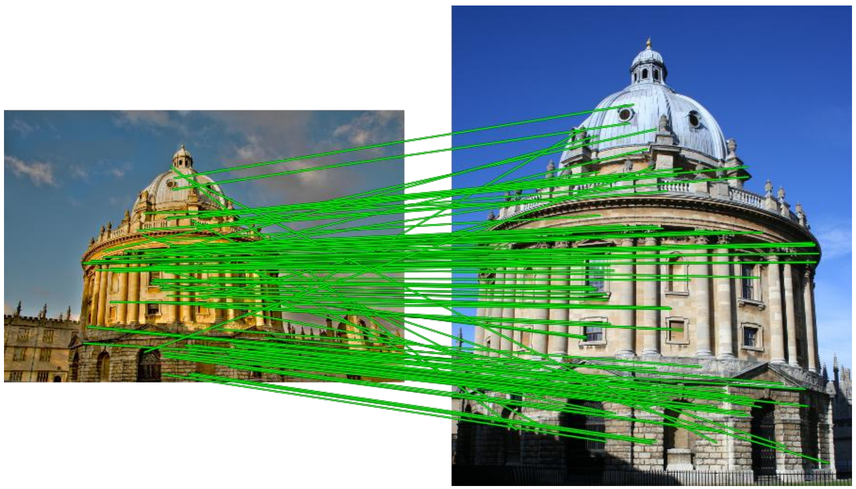


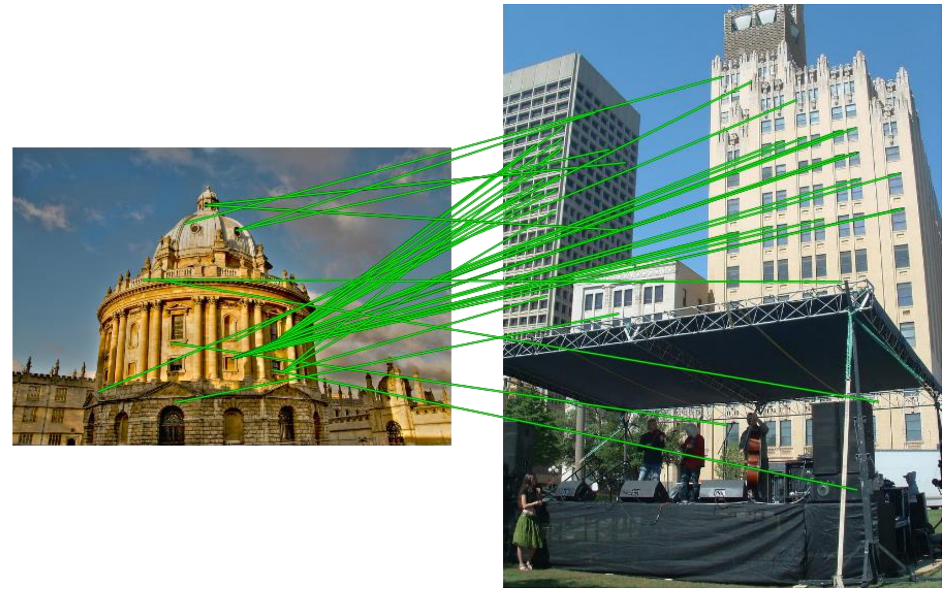
Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras.

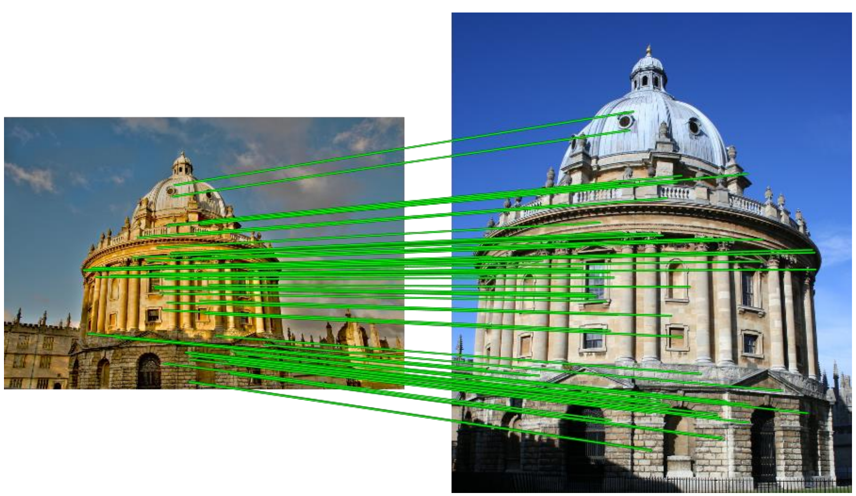
$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

RANSAC verification







Instance recognition: remaining issues

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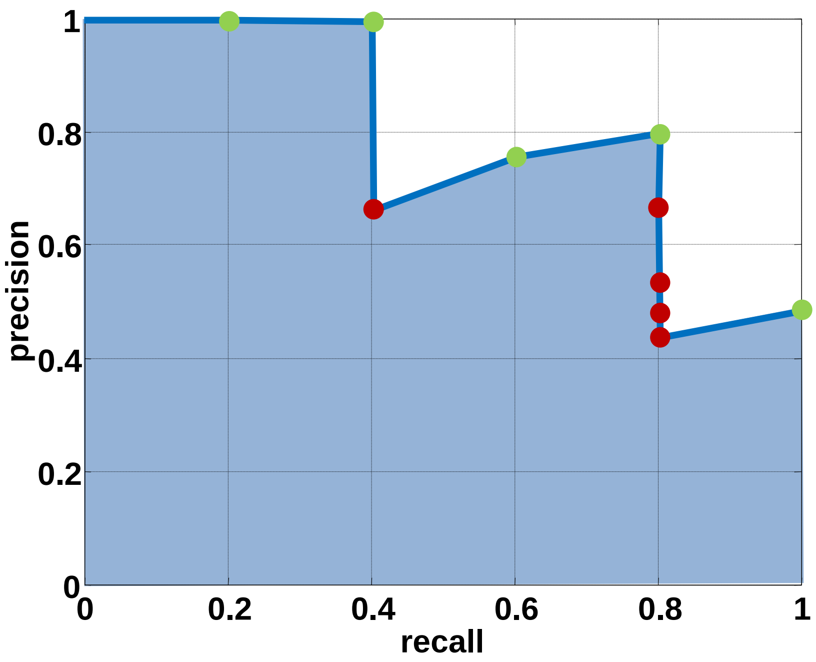
Scoring retrieval quality

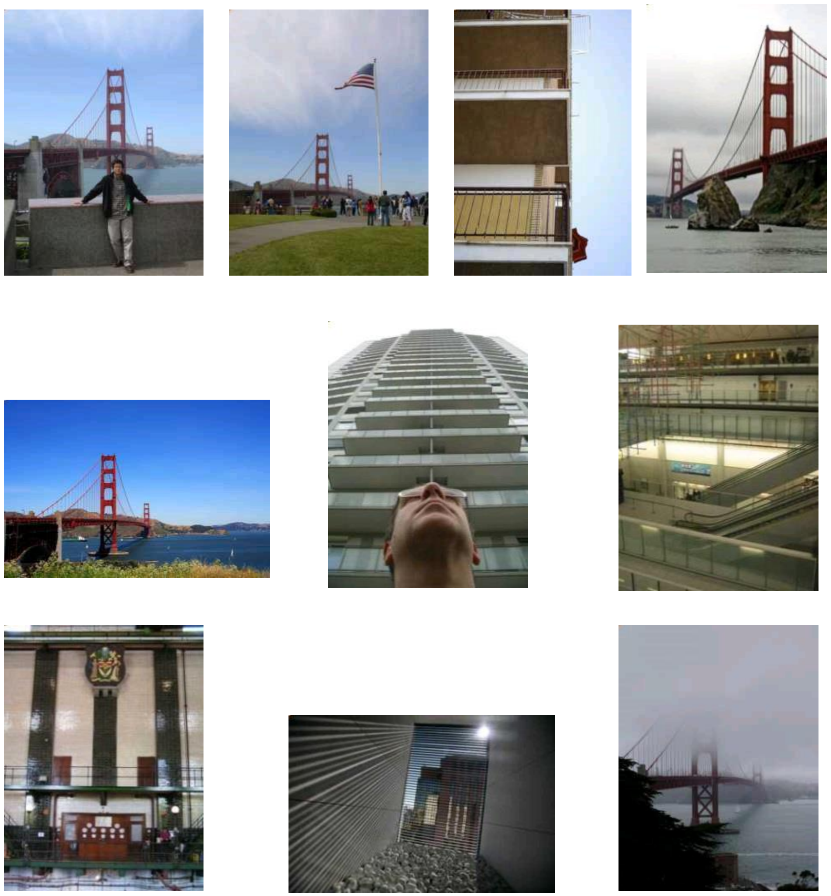
Query

Database size: 10 images
Relevant (total): 5 images

precision = #relevant / #returned
recall = #relevant / #total relevant



Results (ordered):



Slide credit: Ondrej Chum

What else can we borrow from text retrieval?

Index

China is forecasting a trade surplus of $90bn
(£51bn) to $100bn this year, a threefold
increase on 2004's $32bn. The Commerce
Ministry said the surplus would be created by
a predicted 30% ... $750bn,
compared w...
$660bn. T...
annoy th...
China's...
deliber...
agrees...
yuan is...
governo...
also need...
demand so ...
country. China ... e
yuan against the do... nd
permitted it to trade within a narrow ... but
the US wants the yuan to be allowed ... e
freely. However, Beijing has made it c... t
it will take its time and tread carefully be...
allowing the yuan to rise further in value.

tf-idf weighting

- **T**erm **f**requency – **i**nverse **d**ocument **f**requency
- Describe frame by frequency of each word within it, downweight words that appear often in the database
- (Standard weighting for text retrieval)

Number of occurrences of word i in document d

Number of words in document d

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

Total number of documents in database

Number of documents word i occurs in, in whole database

Kristen Grauman

Query expansion

Query: ***golf green***

Results:

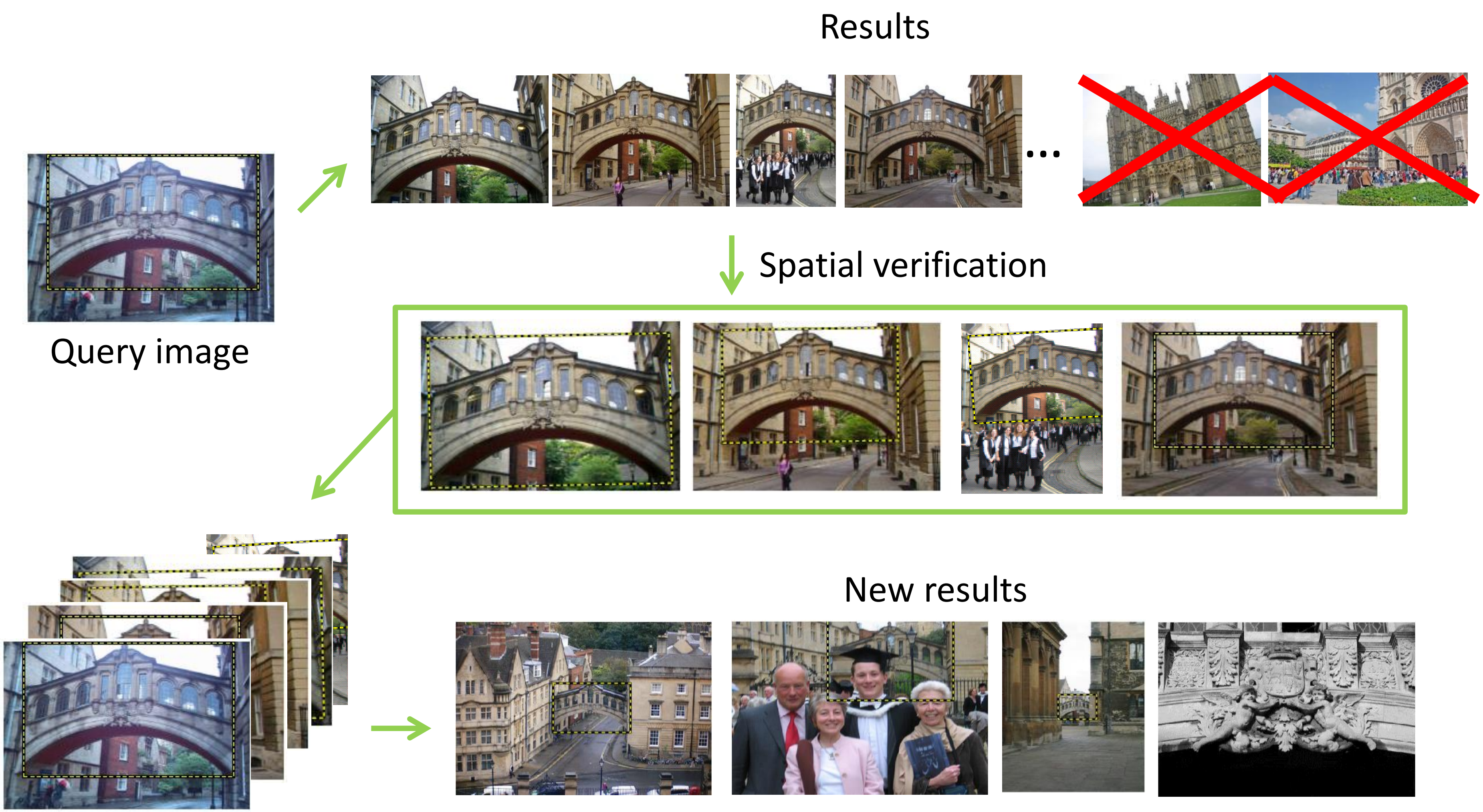
- How can the grass on the ***greens*** at a ***golf*** course be so perfect?
- For example, a skilled ***golf****er* expects to reach the ***green*** on a par-four hole in **...**
- Manufactures and sells synthetic ***golf*** putting ***green****s* and mats.

Irrelevant result can cause a `topic drift':

- Volkswagen ***Golf***, 1999, ***Green***, 2000cc, petrol, manual, , hatchback, 94000miles, 2.0 GTi, 2 Registered Keepers, HPI Checked, Air-Conditioning, Front and Rear Parking Sensors, ABS, Alarm, Alloy

Slide credit: Ondrej Chum

Query Expansion



Chum, Philbin, Sivic, Isard, Zisserman: Total Recall..., ICCV 2007

Slide credit: Ondrej Chum

Recognition via alignment

Pros:

- Effective when we are able to find reliable features within clutter
- Great results for matching specific instances

Cons:

- Scaling with number of models
- Spatial verification as post-processing – not seamless, expensive for large-scale problems
- Not suited for category recognition.

Kristen Grauman

Summary

- **Matching local invariant features**
  - Useful not only to provide matches for multi-view geometry, but also to find objects and scenes.
- **Bag of words** representation: quantize feature space to make discrete set of visual words
  - Summarize image by distribution of words
  - Index individual words
- **Inverted index**: pre-compute index to enable faster search at query time
- **Recognition of instances via alignment:** matching local features followed by spatial verification
  - Robust fitting : RANSAC, GHT

Kristen Grauman

Lessons from a Decade Later

- For *Category* recognition (project 4)
  - Bag of Feature models remained the state of the art until Deep Learning.
  - Spatial layout either isn't that important or its too difficult to encode.
  - Quantization error is, in fact, the bigger problem. Advanced feature encoding methods address this.
  - Bag of feature models are nearly obsolete. At best they seem to be inspiring tweaks to deep models e.g. NetVLAD.

James Hays

Lessons from a Decade Later

- For *instance* retrieval (this lecture)
  - deep learning is taking over.
  - learn better local features (replace SIFT) e.g. MatchNet
  - or learn better image embeddings (replace the histograms of visual features) e.g. Vo and Hays 2016.
  - or learn to do spatial verification e.g. DeTone, Malisiewicz, and Rabinovich 2016.
  - or learn a monolithic deep network to recognition all locations e.g. Google's PlaNet 2016.